7-24-2007

Online Product Information Load: Impact on Maximizers and Satisficers within a Choice Context

Jill Renee Mosteller

PERMISSION TO BORROW

NOTICE TO BORROWERS

All dissertations deposited in the Georgia State University Library must be used only in accordance with the stipulations prescribed by the author in the preceding statement.

The author of this dissertation is:

Jill Renee Mosteller
Marketing Department
J. Mack Robinson College of Business
Georgia State University

The director of this dissertation is:

Dr. Naveen Donthu
Marketing Department
J. Mack Robinson College of Business
Georgia State University

ONLINE PRODUCT INFORMATION LOAD: IMPACT ON MAXIMIZERS AND SATISFICERS IN A CHOICE CONTEXT

BY

JILL RENEE MOSTELLER

A Dissertation Submitted in Partial Fulfillment of the Requirements for the Degree

Of

Doctor of Philosophy

In the Robinson College of Business

Of

Georgia State University

GEORGIA STATE UNIVERSITY
ROBINSON COLLEGE OF BUSINESS
2007

ACCEPTANCE

This dissertation was prepared under the direction of the Jill R. Mosteller's Dissertation Committee. It has been approved and accepted by all members of that committee, and it has been accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Business Administration in the Robinson College of Business of Georgia State University.

H. Fenwick Huss

DISSERTATION COMMITTEE

Dr. Naveen Donthu

Dr. Sevgin Eroglu

Dr. Corliss G. Thornton

Dr. Detmar Straub

ABSTRACT

ONLINE PRODUCT INFORMATION LOAD; IMPACT ON MAXIMIZERS AND SATISFICERS IN A CHOICE CONTEXT

BY

JILL RENEE MOSTELLER

JULY 2007

Committee Chair: Dr. Naveen Donthu

Major Department: Marketing

Information load at various thresholds has been asserted to cause a decline in decision quality across several domains, including marketing (Eppler and Mengis 2004). The influence of each information load dimension may vary by study and context (Malhotra 1982; Lurie 2002; Lee and Lee 2004). Given the explosion of information available on the internet, attracting an estimated 144 million U.S. users (Burns 2006a), this experimental research examined how three dimensions of online product information load influenced consumers' perceived cognitive effort. To the researcher's knowledge, online product breadth, depth, and density have not been empirically tested together, in a multi-page within website context.

A nationwide panel of 268 adult consumers participated in the web-based consumer electronics online search and selection task. Results suggest that a consumer's perceived cognitive effort with the search and selection task negatively influences choice quality and decision satisfaction. Although product breadth directly influenced both choice quality and cognitive effort negatively, cognitive effort mediated product depth's influence on choice quality and decision satisfaction. The perception of informational crowding also negatively influenced cognitive effort.

Additionally, a choice involvement scale was adapted and developed based upon Schwartz's (2004) Maximizer and Satisficer scale. Results suggest that the higher one's choice involvement (tendency toward being a Maximizer), the lower one's perceived cognitive effort with the search and selection task. Both product and choice involvement demonstrated a direct negative influence on cognitive effort, lending further empirical support for the information processing theory of consumer choice (Bettman 1979). A stimulus-organism-response framework, adapted from environmental psychology, was employed to model the relationships among the constructs tested. Results suggest that this framework may be helpful for guiding future online consumer research.

ACKNOWLEDGEMENTS

The author wishes to recognize several people who have either directly assisted or indirectly inspired the creation, conceptualization and completion of this dissertation endeavor.

First, I am deeply thankful for the dissertation committee members who agreed to serve on my committee. The word ‘serve’ is derived from servitude. Each committee member has graciously honored me with their guidance and feedback, which is based upon years of research and academic experience. Collectively in terms of publications, this committee has contributed well over 100 scholarly journal publications. I feel fortunate to have had the opportunity to interact and engage with this committee during my dissertation process. Each member contributed uniquely to my dissertation journey. Dr. Donthu, my chair, helped me manage the entire process efficiently with a warm sense of humor. His guidance has helped me to keep a balanced and thoughtful perspective during this long and sometimes arduous journey. Dr. Eroglu’s enthusiasm, encouragement, and focus on the theoretical foundation of this dissertation provided me a scholarly foundation that will continue to serve me well into the future. Dr. Straub’s expertise in information sciences and experimental design procedures were invaluable. He is truly a mentor to developing researchers. Dr. Thornton’s academic, as well as personal interest, with the Maximizer and Satisficer consumer traits provided thought provoking discussions, contributing to the overall work.

Second, I am thankful to my previous employers, from which the inspiration for this work was partially derived. The ignition for this flame was based in part from seeing consumers experience frustration while trying to accomplish a task online. My hope is that this work will provide some illumination to the business, as well as, the academic community.

Third, I'd like to thank my family and friends, whose continued support, in a multitude of ways, has been heartwarming and inspirational. They supported my dream, even though at times it meant sacrifices, particularly in terms of our time spent together.

Finally, I would like to dedicate this dissertation to my mother, Barbara Anne Guidi. She was an inspirational woman in many ways. She was a successful business woman who frequently exclaimed, 'common sense is not common' and 'Jill, you overanalyze everything'. Well, maybe now I've found my professional home. Mother, may you continue to rest in peace, perhaps now more completely.

TABLE OF CONTENTS

CHAPTER I

INTRODUCTION

Information load has been examined in a variety of business disciplines, including management, accounting, organization science, management information systems (MIS) and marketing (Eppler and Mengis 2004). The overarching theme relates to how a person's performance is impacted by the amount of information one is exposed to (Eppler and Mengis 2004). Research conducted in this area suggests that as the information load increases, decision accuracy will increase up to a certain point, then decline.

Empirical evidence in the consumer choice domain about what causes information load has been somewhat extensive and sometimes equivocal on the results asserted and previous work extended upon (Wilkie 1974; Jacoby, Speller, and Kohn 1974; Scammon 1977; Malhotra 1982; Keller and Staelin 1987; Helgeson and Ursic 1993; Lurie 2002, 2004; Lee and Lee 2004). The number of alternatives and attributes, the quantity and quality, and the structure of information presented have been asserted to influence consumer information load. Consumer information load has been examined in a variety of contexts, most offline. Although decision quality appears to decline at higher levels of traditional and structural load measurements, the influence of each of the dimensions may vary by study and context.

Over the past 10 years information available online has exploded, attracting an estimated 144 million U.S. Internet users (Burns 2006a). Fifty percent of broadband users say the Internet has influenced a recent purchase (Internet Retailer 2007). Seeking information is the second most popular Internet use (e-mail is the most popular use), with more than eight out of ten U.S. Internet users stating they have researched a product or service online (Madden 2003).

Information availability can be considered a key enabler to favorably leveraging and positioning retail strategies (Grewal, Iyer, and Levy 2004). Are there some circumstances however, when too much information presented online may work against retailers? At first glance, the answer may be no. Recent data indicates that U.S. consumers spent $143 billion dollars online in 2005 (Marketing Sherpa 2006) with retail spend (excluding travel) accounting for over 66% (Burns 2006c) In addition it is estimated that U.S. cross-channel shoppers (search online/buy offline) contributed to $125 billion dollars in offline sales in 2005 (Mendelsohn 2006). The percentage of Americans who say that the Internet has greatly improved their ability to shop has doubled from 16% to 32% (Madden 2006). So online consumer expenditures are increasing and more people are using the Internet to shop and search for information.

Customer satisfaction with the online shopping experience, however, declined recently, attributed in part to consumers not being able to find what they were looking for (Burns 2006b). Information abounds on the Internet, but could information presentation be an enabler as well as a hindrance within the search and selection process?

Information attended to on the Internet has important implications. Information presented may influence consumer choice and if online information is not considered helpful, use of that information and the associated web site may decline over time. Despite information availability and personal convenience, consumers may become frustrated and dissatisfied when they are not easily and effectively able to accomplish their shopping tasks (Burns 2005f). Impact may include reduced long term sales potential based upon decreases in shoppers' likelihood to return and recommend the web site (Burns 2005f).

PURPOSE OF STUDY

Factors that influence how a person may cope with environmental input may be a function of the difficulty of the task, the amount of interaction, the individual's personal characteristics, and one's previous experience and prior expectations (Harrell and Hutt 1976). Understanding how individual characteristics may interact with online product information to manifest variance in perceived cognitive effort with the product search and selection task is one purpose of this study. If high cognitive effort is exerted, how it may influence product choice, search time, and decision satisfaction may have important practitioner and academic implications.

From an academic standpoint, there are five interesting questions. One is a contextual extension of existing theory. Specifically how does the depth of product information influence the perceived cognitive effort of consumers? One of the unique attributes of the Internet, as compared physical store contexts, is that the Internet may be more cognitively demanding of consumers (Chiang 2003). Using the Internet typically requires reading and attending to detailed information through a series of web pages over a prolonged timeframe. The information contained in a website is considered to be a key facet within a web site that determines its perceived usefulness (Argawal and Venkatesh 2002). Visual perceptiveness, reading, comprehension, concentration, and manual dexterity could be considered especially important skills when shopping online (Olson and Olson 2003). Offline, one can engage all of the perceptual senses (sight, sound, smell, touch, and taste) to perceive the environment more holistically. Thus the visual information perceived online may take on particular importance in shaping consumers' online shopping experience (Chau, Au, and Tam 2000). Previous research suggests that how information is presented influences decision-making processes (Payne, Bettman, and Johnson 1993).

A second issue of interest is the empirical testing of spatial crowding and its influence on cognitive effort as an online atmospheric variable. Although the Internet may be loaded with information, how the information is presented spatially is posited to influence cognitive effort. Online design techniques (e.g. spacing of information) that attenuate cognitive effort may be perceived more favorably by online shoppers. Ease of use, the cognitive effort required in using a website (Argawal and Venkatesh 2002), has been positively associated with intentions to use various types of technology. Is there a related construct that describes the cognitive effort with which a person can process and evaluate information – a cognitive ease of use per se – that better predicts decision satisfaction outcomes from exposure to information stimuli? This dissertation will attempt to answer this question.

The third interesting issue is the refinement and better understanding of what influences consumers to experience an increase in information load when examining product information online. Research suggests the structure of information is a better predictor of consumer information load, other research suggests structure and attribute depth both contribute (Lurie 2004; Lee and Lee 2004). This research will examine three different dimensions of product information load, specifically product breath (number of products), depth (number of features), and density (words per page) that may contribute to perceived consumer information load and see how this may relate to perceived cognitive effort with the product search and selection task.

The fourth research question is the development and nomological testing of the construct, cognitive effort, as a mediator between online environmental stimuli and consumer outcomes. This study will test if a person's perceived cognitive effort may be a better predictor of choice quality outcomes than traditional information load measures. How cognitive effort may manifest variability with decision satisfaction will be one outcome examined. Previous studies examining cognitive effort have used objective criteria, like the number of elementary information processes (EIP's) used or time as a proxy (Garbarino and Edell 1997; Bettman, Johnson and Payne 1990) for cognitive effort, not perceptual factors. Total time spent on the task is a second outcome to be examined. How time spent on the task correlates with cognitive effort, choice quality and decision satisfaction under different load conditions may provide additional insights.

A fifth research question is examining how the situational trait of product involvement and the enduring trait of choice involvement (the Maximizer/Satisficer) may influence the perceived cognitive effort experienced while performing the online search and selection task. The Maximizer and Satisficer trait has had little empirical testing within the marketing domain (Schwartz 2004; Schwartz et al 2002), but may be highly appropriate within the proposed framework and context. Retailers may offer a larger assortment of products online than offline, due to lower associated costs. Schwartz (2004) suggests that the plethora of consumer products available may elicit Maximizer tendencies.

From a managerial perspective, insight may be gleaned on how online product information may influence consumer shopping states and choice outcomes. These findings may help online marketers to enhance product positioning with the consumer, so that desired outcomes are enhanced. Time spent during the search and selection task may provide insight into customer purchase intent and/or if the website is meeting consumers' needs. Too little, as well as too much time spent on the web site may indicate dissatisfaction (not finding what they are searching for or inability to easily navigate or process information presented). Historically a web site's success may have been evaluated on the increase in new visitors and the total number of visitors (Moe and Fader 2004). Ironically, a website may be viewed as successful because the ratio of purchases to unique visitors is increasing and time spent on the site is decreasing (inferring efficiency), however if the post consumption experience creates consumer regret, what may be viewed as a successful consumer experience, may lead to dissatisfaction in the long run. If the consumer feels that an inferior selection was made, the likelihood of revisiting the site may be attenuated. Too much information may influence consumer choice from irrelevant attributes, which then may result in post selection regret, impacting future patronage intentions (Thompson, Hamilton and Rust 2005). Examining how actual choice quality and decision satisfaction correlate as outcomes may have interesting practitioner implications regarding short term sales and long term customer loyalty.

In sum, this study examines product information properties that create variance in cognitive effort for consumers as they search through pages of product information online. Is perceived cognitive effort within a search and selection task an important mediator that will help to better predict online consumer behavior decision satisfaction outcomes? How do consumer product and choice involvement influence cognitive effort? How does the personality trait of being a Maximizer or Satisficer moderate the effects of information load? This research will attempt to provide additional insight to these questions.

CHAPTER II

LITERATURE REVIEW

INFORMATION LOAD

The concept of information load has been examined in a variety of business disciplines, including management, accounting, organization science, management information systems (MIS) and marketing (Eppler and Mengis 2004). The overarching theme among all of these disciplines relates to how a person's performance is impacted by the amount of information one is exposed to (Eppler and Mengis 2004). Research conducted in this area suggests that as the information load increases, decision accuracy will increase up to a certain point, then decline. The point where the slope of the curve becomes negative indicates when information overload occurs. Considerable debate on how and if this empirical manifestation occurs has been published (Wilkie 1974; Jacoby 1977; Scammon 1977; Malhotra, Jain, and Lagakos 1982; Jacoby 1984; Malhotra 1984).

The first empirical work in marketing to examine information load was by Jacoby, Speller and Kohn (1974). At the time public policy issues centered on consumer advocacy and information disclosure around product labeling. Information load was operationalized as the number of alternatives and the number of attributes per alternative. Results suggested that information load was positively associated with various outcomes; decision satisfaction, certainty of best decision and increased levels of confusion during the task. As the number of alternatives increased, decision satisfaction also increased. As the number of attributes increased, subjects were more certain and less confused while making their decisions. Measurement issues raised by peers in this experiment's results were addressed in another experiment conducted by the same group of researchers that expanded the level of brands and attributes and used housewives versus students as subjects (Jacoby, Speller, and Kohn-Berning 1974). Accuracy in product selection was based upon the distance from the ideal product and time required to reach a decision. Information load was positively associated with time to reach a decision and again, negatively associated with decision accuracy. The dialogue and debate ensued around many issues, including questioning if people ever indeed suffered from an overload of information or if they adapted by attending to less information, resulting in poorer decisions (Jacoby 1977; Scammon 1977).

Malhotra (1982) addressed methodological and analytical issues previously raised by taking into account variance in probabilities based upon the number of alternatives available to subjects within an experimental condition and expanded the information load range. He measured objective as well as subjective measures of information load. Results suggested that as the number of alternatives increased, the probability of making the correct (best) choice declined, factoring in probabilities based upon the number of alternatives in each experimental condition. A key finding was that the number of alternatives and the number of attributes were distinct and independent dimensions of information load. Each had a main effect on decision quality once the quantities of each reached certain thresholds. Specifically when the number of attributes exceeded 15 and the number of alternatives exceeded 10 is when dysfunctional consequences occurred. No interactions effects were detected, however the sample size per cell (n=12) may not have large enough to detect moderating effects (Kirk 1995).

Keller and Staelin (1987) refined previous work by examining how information quality (the cumulative importance of information) as well as quantity impacted decision effectiveness and consumer confidence. The percentage of information used was positively associated with decision accuracy. When the average quality of information was held constant and the quantity of information (number of attributes) was increased, decision accuracy declined. When the quantity of information was held constant and the quality increased, the percentage of information used increased but the accuracy of decisions also declined. Quality alone had a positive effect on decision effectiveness, quantity alone a negative effect. Additionally, increases in quality, holding quantity of information constant resulted in greater consumer confidence. Holding quality constant and increasing quantity reduced consumer confidence. So in sum, the quality of information helped decision making up to a certain point, but beyond a certain threshold dysfunctional consequences emerged.

Helgeson and Ursic (1993) expanded upon previous work taking into consideration task and context effect variables. Task complexity effects were operationalized by the number of alternatives and attributes per alternative one had to sort through. The range varied from 16 pieces of information (four alternatives with four attributes each) to 64 pieces of information (8 alternatives with 8 attributes). So in essence 'task' effects were different levels of information load. Simple tasks represented low information load conditions. Complex tasks operationalized high load conditions. Context effect variables were operationalized by alternative and attribute similarity, creating a 2x2x2x2 between subjects experimental design. Outcomes examined were decision strategies used, decision accuracy, and decision time. Results indicated that as the number of attributes and alternatives increased (higher task complexity), time to make a decision increased. Also alternative similarity was positively associated with decision time. This may be attributed to subjects having to become more detailed in their comparisons given that differences were less apparent. Decision-making accuracy was negatively related to the number of attributes and alternative similarity. These results support previous research that the number of attributes contribute to information load and extend work in the area by demonstrating that product similarity may also contribute to strain in the decision making process.

Up to this point information load had been operationalized in an offline context, utilizing students, housewives, and adult subjects appropriate for the product(s) selected for the experimental conditions. Theoretical frameworks using information processing and decision-making were used to predict assertions and in some cases extend theory. Next we will discuss research conducted online using the information load construct.

ONLINE INFORMATION LOAD

Research examining how information load may influence end user outcomes in an online context includes information management, management, as well as marketing domains. Relevant research within each of these domains will be discussed.

From the information management domain, Huang (2000) operationalized information load on two dimensions, novelty and complexity, pulling from the environmental psychology literature (Mehrabian and Russell 1974). Environmental psychology researchers have typically used the stimulus-organism-response framework to guide research. Typical behavioral responses measured have been approach-and-avoidance behaviors. In this research subjects visited web sites and then reported their responses. Subjects reported their perceptions of the web site with regard to novelty and complexity (operationalized as information load) and their subsequent desire to explore and shop on that site. A decreased desire to shop and/or explore was considered avoidance, and increased desire was considered approach. Information presented that was perceived as contrasting, surprising, and rare was high in novelty. Information that was considered complex, crowded, and of a large scale was scored as high on complexity. Together these two dimensions of complexity and novelty formed information load. Complexity was negatively associated and novelty positively associated with the desire to explore (approach) the website. Complexity was positively associated with the desire to shop, however the relationship was weak (p=.07/1.68) (Huang 2000). These results suggest that how information load is operationalized is critical in determining or predicting different outcomes. In this case the two dimensions acted in counterbalancing ways, which could have lead to insignificant results if they could not have been tested individually. The interesting finding, although not robust, is that complexity may be perceived as favorable if one visits a web site with the intention of buying. Perhaps the large selection is perceived as being a favorable attribute (e.g useful in accomplishing a task) when searching for a particular product, however, if the intention is more recreational (e.g. browsing/hedonic), the large selection may not be perceived as pleasurable, but more of a headache to navigate through.

Menon and Kahn (2002) also used the environmental stimulus response framework but used three dimensions: novelty, complexity, and intensity. These three dimensions operationalized 'arousal' in an online setting. Although Menon and Kahn do not explicitly call their independent variables 'information load', 'arousal' is similar to the way in which the 'stimulus' of information load has been operationalized using the environmental psychology framework. Novelty was operationalized as the variance in the types of books offered (breadth of categories) which can be described as the degree of similarity. Complexity was operationalized as the degree of clutter in the layout (amount of non-relevant information), which could also suggest the degree of 'quality' of information presented. Intensity referred to the visual atmospherics (e.g., bright colors) and the quantity of information (high quantity = high intensity). So information similarity, quality, and quantity were operationalized as stimulation variables in this experiment. The context of the study was subjects browsing within and between sites in an online shopping mall. Results suggest that high stimulation is negatively associated with approach behaviors.

Suri, Long, and Monroe (2003) sought to better understand how task motivation combined with information load affected price and value perceptions of products presented online. This research was spurred on by anecdotal evidence that consumers may be willing to pay more for products purchased online, than less. Their educated guess was that the information load online might be a contributing factor. Their research operationalized information load only by the number of alternatives. Seven and nineteen alternatives represented the low and high information loads respectively. It should also be noted that subjects simply had to view a one-page computer screen to compare alternatives. There was no interaction or maneuvering through web pages in the study. Chaiken's (1980) Heuristic Systematic Model (HSM) guided the study. Results suggested that even under conditions of high motivation, high information load might have caused subjects to resort to heuristic methods of assessing value, by using price as a proxy (e.g. high price = high value). Under low information load conditions, a more systematic appraisal of value may have been used, thus not assessing higher priced products as having necessarily greater value. These results suggest that choice online may be attributed to consumers' method of processing information, influenced in part by the online informational conditions.

The Academy of Management best conference paper for 2004 tested how user tasks (goal/experiential) moderate the relationship between perceived website complexity (PWC) and telepresence (Nadkarni and Gupta 2004). Perceived website complexity was defined as information cues, within a site, that are dissimilar and visually dense. Thus crowded and unrelated information within a web site was posited to create higher perceived complexity on users than uncluttered and congruent informational cues. Subjects were assigned to one of 48 pre-selected web sites. Half of the subjects were assigned to browse, the other half to find. Results suggest that task type moderates the relationship between perceived website complexity and telepresence. Under conditions of high perceived website complexity, task-oriented users experienced lower telepresence. Experiential shoppers reported telepresence in an inverted U form as perceived website complexity increased. Telepresence mediated web site user attitudes for goal and experiential users. The theoretical framework guiding the assertions was Cognitive Load Theory (Steuer 1992), which suggests that processing visual and verbal cues is cognitively demanding. Given the multiple pages of visual and verbal cues processed within a web site, effects that make the information more difficult to process will require more cognitive effort.

Chiang (2003) uses information load as an independent variable and operationalized it by the number of web sites the subject has to search through in the assigned task. Low load is six sites, high is 50. This research compares search costs between store and web sites. Online cognitive search efforts are asserted to be taxing, thus mitigating extensive searches by consumers, even though another site is physically only a click away. Domain expertise, not information load was found to contribute to the amount of variance in search efforts. Semantically cognitive search costs could be similar to cognitive effort. Upon closer inspection, it does not represent the conceptualization. Cognitive search costs consisted of four scale items that were summed: amount of product information, quality of product information, reputation of retailers, and finding the lowest price.

As the research on information load has evolved, empirical studies have attempted to clarify what informational attributes elicit variance in the amount of information processed. Lurie (2004) suggests based upon a series of studies that it is the structure of information that contributes to variance of amount of information processed, leading to variance in choice quality outcomes. His research suggests that the number of levels within an attribute and distribution levels within an attribute influence the level of information load experienced. Results suggest that uneven attribute levels mitigate information load as compared to even distribution of attribute levels across alternatives. What this means is if there are nine alternatives and three levels of an attribute (e.g. warranty – 30, 60, 90 days), even distribution of an attribute level would indicate that three alternatives have a 30 day warranty, three have a 60 day warranty, and three have a 90 day warranty. An uneven distribution of attribute levels from the previous example may be that one alternative has a 30-day warranty, two alternatives have a 60-day warranty and six alternatives have a 90-day warranty. Study two suggests that an increase in the levels of attributes also lowers decision quality. As the amount of information increased, the time spent per acquisition also increased. The information structure and load were mediated by the decision rule used. Lurie's contribution in this area is he has empirically applied a mathematical formula that better predicted choice outcomes than previous conceptualizations of information load. He has refined how information load may be measured objectively on four dimensions that appear to better predict choice quality outcomes. The online context used was a matrix positioned on one page, displayed on a computer screen.

Lee and Lee (2004) compare traditional and structural approaches to information load; in addition they extend Lurie's work by manipulating the levels of attributes. Like Lurie's study, the experiment context was an online matrix that displayed the entire set of product alternatives simultaneously on one a one-page computer screen. The product was a portable CD player that the subject selected for a friend and each subject had two minutes to complete the task. After two minutes the matrix disappeared from the screen. The experiment was a 2x2x2 between subjects design with number of alternatives (18, 27), number of attributes (9, 18) and distribution of attribute levels across alternatives (equal, unequal) being the independent variables. Contrary to Lurie's results, increasing the number of alternatives from 18 to 27, holding everything else constant, did not significantly decrease the probability of making a correct choice. Mathematically, the differences in the amount of information bits as calculated by formal information theory between 18 and 27 alternatives, with the other two conditions being the same, was not significantly different. Logit regression analysis, accounting for chance, was not significant for the alternative coefficient. The increase in number of attributes from 9 to

18, however, did significantly increase the probability of decreasing choice quality. Uneven distribution of attribute levels across alternatives also increased the probability of increasing choice quality, supporting Lurie's assertions. The number of attributes and attribute level of distribution did produce significant results with regard to choice quality and were better predictors of information overload than the number of alternatives. Regarding subjective states, subjects felt more confused, less confident, and less satisfied with 18 attributes versus 9. With 27 versus 18 alternatives, subjects were less confident and more confused. Subjects exposed to unequal distribution levels were more confident in their decision than those exposed to equal levels of distribution. In sum, the results provided partial and full support for previous work on information structure. A key difference is the impact that varying the number of attributes per alternative had on choice outcomes and subjective states.

In sum, previous research suggests that the study of information load has made progress in the past 20 – 30 years. Although decision quality appears to decline at higher levels of traditional and structural load measurements, the influence of each of the dimensions may vary by study and context. Information load has been operationalized in different ways, however manipulating the number of alternatives and/or attributes among treatments is common across many studies. What has been less consistent is the way in which choice quality is determined. A review of choice quality will now be discussed.

CHOICE QUALITY

Choice quality is generally defined as the quality of choice made given the alternatives available. The best choice may be determined by that which has the greatest weighted additive utility. As an example Lurie (2004) used the following:

$$\text{Choice Quality} = \frac{\text{Weighted Additive Value (WAV)}_{\text{Choice}} - \text{WAV}_{\text{Worst}}}{\text{WAV}_{\text{Best}} - \text{WAV}_{\text{Worst}}} \quad \text{(Equation 1)}$$

Equation 1 produces a range from 0 to 1 with 1 indicating the best choice. So the closer the choice quality is to one, the better the choice. Choice proportions are generally adjusted for chance factors following Malhotra's (1982) recommendation. Proportion of correct choice adjusted for chance ($\underline{P}_i$) is calculated as follows:

(Observed proportion – Proportion by chance alone)/(1 – Proportion by chance alone)

Pi = (Pi - Pic)/(1 - Pic)

In order to have an objective 'best' choice, one option is to have everyone use the same weights assigned to the different attributes. This is accomplished by providing subjects with the predetermined weights. Scenarios may include choosing a product on behalf of a third person's preferences, and/or by using a third party source like consumer reports (Lee and Lee 2004; Lurie 2004). This approach ensures that the best choice is unambiguous (Diehl 2005). Another option is to have subjects state their weighted preferences (e.g. assign 100 points among the attributes listed) and calculate the best choice for each subject, assuming compensatory processes are being used to reflect 'decision effectiveness' (Keller and Staelin 1987). The ideal choice assumes that all information presented will be used to make a decision and the best alternative comes closest to the subject's ideal alternative (Keller and Staelin 1987; Malhotra 1982). Euclidian distances between the ideal and choice set are computed and the alternative with the shortest distance is considered the optimal choice (Jacoby, Speller and Kohn 1974; Malhotra 1982). A satisficing choice measure has been operationalized by as either the closest or second closest to the ideal alternative (Malhotra 1982).

Through a series mathematical steps, Keller and Staelin (1987) calculated task ease (TE) for each condition based in part on the cumulative differences in total utilities for each of the alternatives available. The best choice total utility score started the equation followed by subtracting the utilities from the second best choice and so on. Large utility differences between alternatives would imply a large TE score, meaning the task was easier as compared to when differences between alternatives were small (given the same number of alternatives), which would calculate a smaller TE score, implying selecting the best alternative would be more difficult. They used this objective measure of task ease as a variable in regression analysis, in addition to amount of information and the quality of information to determine a satisficing choice quality outcome.

Meyer and Johnson (1989) questioned this model and reanalyzed Keller and Staelin's data. Their conclusions raised some speculation about the accuracy of the model and concluded that there will always be measurement error when using models to define optimal decision (Keller and Staelin 1989). Interestingly Keller and Staelin's formula relates with the concept that similar products are harder to distinguish, thus requiring more cognitive effort to distinguish differences in order to make a decision for selection. Earlier work may have determined best choice by selections that had the least difference between the ideal choice and the actual choice (Jacoby, Speller, and Kohn 1974) or by using part worth utilities following an additive compensatory rule (Keller and

Staelin 1987). Rank order accuracy was another method (Jacoby, Speller, Kohn-Berning 1974).

In sum, the operationalization and calculation of choice quality across various experiments has not been without active dialogue and discussion. Designing a study that avoids the use of individual personal preferences and creating an alternative that is a superior choice based upon objective standards appears to be the most experimentally robust approach.

CROWDING

Perceived crowding has been defined as a psychological state that occurs when a person's demand for space exceeds the supply (Stokols 1972). Crowding may refer to the number of people, objects, or both in a limited space that restricts or interferes with an individual's goal achievement (Machleit, Eroglu, and Mantel 2000). The key point is that crowding is a perceived and subjective state (Eroglu and Harrell 1986). Early empirical studies used variance in densities of people and objects to see how these atmospheric variables elicited perceptions of crowding (Harrell, Hutt, and Anderson 1980; Eroglu and Machleit 1990). Eroglu and Machleit's (1990) simulation study suggests that high retail density is positively associated with perceptions of retail crowding, of which is particularly accentuated under goal oriented task conditions. High retail density combined with time pressure was negatively related to shopping satisfaction. Hui and Bateson (1991) found that consumer density directly and positively influenced perceptions of crowding. Perceived control was also found to attenuate perceptions of crowding, which may suggest implications in an online environment (Hoffman, Novak and Schlosser 2003). In Machleit, Eroglu and Mantel's (2000) study, spatial crowding was associated with negative feelings and a decline in shopping satisfaction.

The concept of crowding has been classified as an environmental variable in research that may interact with a person to produce a behavioral response (Stokols and Altman 1987). One framework used in empirical studies has been the Stimulus-Organism-Response model in offline (Hui and Bateson 1991; Huang 2000), as well as online contexts (Menon and Kahn 2002; Eroglu, Machleit, and Davis 2003). The stimulus within this framework can represent a variety of factors from people, objects, color, music etc. The responses measured can vary as well. Table 1 provides a relevant summary of factors used in the Overload Model of Crowding. Environmental factors within the overload model have included the number of interactions, spatial construction, and environmental demands. Mediators tested include one's perceived intensity, complexity, novelty and unfamiliarity of the environment, with the responses including one's attention allocation, attention capacity, and cognitive fatigue.

Overload Model of Crowding

Saegert's (1973; 1978) work suggests that high-density environments increase the demands on peoples' attention capacity. Milgram (1970) discusses overload in terms of systems analysis. Specifically as the number of people increase, the overall involvement allocated to each individual decreases. When demand exceeds capacity, overload occurs and adaptive responses ensue. The same could apply to information. As the information presented increases, the allocated attention required by an individual to process the stimuli increases. When attention effort required exceeds capacity, overload will occur and adaptive responses like selective screening of stimuli may result and/or feelings of cognitive fatigue (Cohen 1978; 1980). So the overload model, focusing on the number of interactions (e.g. the number of web pages and products viewed), the spatial construction of information (the number of features and wording associated with each feature), and the environmental demands (e.g. task oriented) aligns with the operationalization of the three independent variables proposed. Information breadth, depth, and density are forms of online visual stimuli. The interaction of these stimuli with the subject is posited to create responses.

The environmental stimulus, organism and response framework may be conducive for online contextual research because one form of behavioral response can be captured with clickstream data (Menon and Kahn 2002). Capturing the depth (the number of pages explored within a site) and breadth (the number of different sites explored) and the respective lack thereof may operationalize approach and avoidance behaviors. In terms of environmental stimulus, Huang (2000) used novelty and complexity to operationalize information load. Complexity reflected three factors; degree of complex information, the scale of information, and the degree of crowdedness. Novelty reflected dimensions of being surprising, rare, and contrasting. Each dimension had a different impact on behavior. Complexity was negatively associated with the desire to explore, whereas novelty had a positive relationship. Eroglu, Machleit and Davis (2003) found that online stimuli (e.g. color, pictures) that elicited pleasure were positively related to approach behaviors. Pleasure is one of the emotional responses modeled by Mehrabian and Russell (1974) in environmental psychology that is posited to precede behavioral outcomes. In a previous offline study, spatial crowding was negatively related to pleasure (Machleit, Eroglu, and Mantel 2000).

In sum the concept of overload suggests that when the amount and rate of environmental input exceeds one's capacity to cope, behavioral adaptation will occur (Harrell, Hutt, and Anderson 1980). The environmental input can be a wide variety of factors that captures an array of different dimensions. Approach and avoidance behaviors from the stimuli are two outcomes that have been modeled. As Kotler (1973) stated, retailers should focus on designing buying environments that enhance purchase probabilities. The design of the online retail web site should be no different; however, retailers need to be mindful of other buyer effects that their online merchandise presentation may be evoking. Online atmospherics has been defined as the "the conscious designing of space to create certain buyer effects" (Eroglu, Machleit, and Davis 2003). Atmospheric effects elicited from informational presentation factors are explored in the proposed study. Factors that influence how a person may cope with environmental input may be a function of the difficulty of the task, the amount of interaction, the individual's personal characteristics, and his/her previous experience and prior expectations (Harrell and Hutt 1976). Next research covering the various cognitive effects from being exposed to stimuli will be discussed.

COGNITIVE LOAD AND INFORMATION PROCESSING

Limited Working Memory

Research and discussion about how people process information and their respective limitations can be dated back to at least 1956 when George Miller wrote "The Magical Number Seven, Plus or Minus Two: Some Limits on Our Capacity for Processing Information" (Miller 1956). He summarized experiments conducted up to that time that covered a variety of domains, from musical tone and pitch recognition to the recall of visual displays used in the Air Force. With one-dimensional stimuli he suggested that people possess a small and finite capacity for making one-dimensional judgments. He proposed that the "span of absolute judgment is somewhere in the neighborhood of seven." (Miller p. 348) with implications being that people are limited in their ability to receive, process, and remember. In order to manage these limitations, methods of measuring the load of stimuli presented were suggested.

Processing Capacity

The concept of a limited working memory is incorporated and expanded upon in the Information Processing Theory of Consumer Choice (Bettman 1979). Within this framework, processing capacity plays a pivotal role. Factors suggested that influence one's processing capacity are motivation and the attention one allocates to the information. One who is highly motivated is posited to exert more effort, thus positively influencing processing capacity allocated to the task. An increase in processing capacity may result in greater attention being directed toward the stimulus, thus influencing the information that is acquired and evaluated in the decision making process.

The relationship between attention and processing capacity is reciprocal, meaning that the greater the attention given to a stimulus, the greater the pull on the processing capacity's resources. Conversely, a decrease in processing capacity may result in one attending to less information, thus acquiring and evaluating less information, and influencing decision processes because of the information used (or ignored) to make a choice. Thus processing capacity is posited to directly and indirectly influence decision processes. Processing capacity indirectly affects decision processes through its impact on attention, information acquisition and evaluation. Processing capacity is also posited to influence the goal hierarchy. How all this relates to the choice outcome is that goal hierarchy provides the steps necessary to achieve the desired state. As a result, one's attention focuses on that information that is perceived to be relevant for the task at hand. The assumption is one's goal hierarchy governs one's attention (Bettman 1979). This framework suggests that the amount, the rate, and how the information presented may influence how the person is able to process the information (Painton and Gentry 1985).

Another influential factor is one's level of motivation to process the information. The perceived relevancy of the information is to one's established goals may influence the level of processing allocated. If the information presented exceeds the person's ability to process, cognitive overload may occur (Jacoby 1984; Baum and Paulus 1987; Eppler and Mengis 2004). The proxy indicator for cognitive overload has been the point where decision quality declines. Subjective states have been captured as outcome variables when exposed to stimuli.

Cognitive States

The previous discuss raises the question of how one's cognitive affect state during the decision-making process may influence the quality of the decision outcome. One could describe it as the cognitive-affect state during the process of processing information. As Turley and Milliman (2000) explain, "atmospheric variables can be conceptualized as stimuli leading to some cognitive affect within the individual, which in turn, leads to some behavioral response" (Turley and Milliman 2000, p 194.) The context of their statement refers to a bricks and mortar store. So, an extension of this work would be to test how 'the conscious designing of space' (Eroglu, Machleit and Davis 2003) with information create online atmospherics. Specifically how the sequence, spacing, and format of the information affects the cognitive state of a person. Given the intensive information available on the Internet, the discussion will now focus on cognitive studies within the Human-computer interaction (HCI) literature.

"Human-computer interaction is the study of how people interact with computing technology" (Olson and Olson 2003, p 492). The human-computer interaction (HCI) field includes the field of cognitive psychology, in addition to other social sciences. Cognitive modeling attempts to understand in detail the involvement of the cognitive, perceptual and motor components in the moment-by-moment interaction a person has when interacting with a computer (Olson and Olson 2003). This approach in part, attempts to better understand and predict what choices people will make when faced with alternative methods. An overarching framework is the executive process-interactive control (EPIC) by Kieras and Meyer (1997) (as cited by Olson and Olson 2003). Components of the model include task environment, working memory, visual and auditory inputs and visual and auditory processors. All these factors are posited to facilitate, in part, the moment-by-moment interactions, perceptual processes and responses.

So human-computer interaction field is not distinctly different from information processing as discussed in the marketing literature. The EPIC framework is different in that it overtly acknowledges the visual and auditory inputs and processors as distinct contributors to behavioral outcomes. The implication is that in the online context, visual cues may take on a more prominent influence as compared to other shopping contexts. Like cognitive modeling, the development and testing of the construct cognitive effort will attempt to better understand how a person's cognitive and perceptual involvement interacts with the visual stimuli online in a given a task situation to see the perceived cognitive and affective states it may elicit.

COGNITIVE EFFORT

Cognitive effort is defined in this study as one's perceived degree of cognitive effort required, in order to accomplish a task, using the information presented. Variance in perceived cognitive effort among individuals given the same informational stimuli is likely. One factor may be a person's product, task, or decision making experience, thus pulling additional informational sources from long-term memory when processing information and making a decision. Individual and situational factors may also influence the informational processing efficiency of subjects (Moschis and Mosteller forthcoming), thus resulting in the variance of cognitive effort exerted. Individuals with lower processing efficiency may find the same task more cognitively effortful than others who are able to process information more efficiently.

Ease of Use

Related concepts to cognitive effort have been used in various domains. In the information sciences literature ease of use (EOU) is a common construct, typically associated with the technology acceptance model (Davis 1989; Venkatesh and Davis 1996; Gefen and Straub 2000). One could assert that ease of use may be on the positive side of the same scale, with high cognitive effort on the negative affect side. Cognitive effort would be the overall scale descriptor. High cognitive effort denotes effort and low cognitive effort denotes ease of use. Another perspective is that a person who scores a system low on ease of use could be interpreted as the system or technology is hard to use, although that may not be what the respondent meant. That's an assumption the researcher would prefer to address directly by constructing and testing factors and developing scales that directly address the research questions proposed, although using and testing items from related scales in the scale and construct development.

A key distinction between ease of use and cognitive effort is that cognitive effort is focused on the task and how the information stimulation may facilitate or hinder the processing of information. So questions relating to the 'system' may be inappropriate given that the system investigated is one's processing capacity interacting with visual stimuli. Although one could counter-argue that the 'system' is a combination of the person and the computer generated information. A one-dimensional scale could be anchored with perceived task ease and task strain. Keller and Staelin (1987) modeled task ease as a function of information quantity and quality, with quantity of information having a negative influence and quality of information a positive influence on task ease. This framework suggests that information that helps to differentiate alternatives (quality) while not being taxing on processing capabilities (quantity of information attended to), would elicit greater task ease, thus demanding fewer cognitive resources (less cognitive effort) than information that was very similar and in great quantity.

This discussion suggests that the factors that may contribute to the development and measurement of cognitive effort may be related to the ease in which one was able to accomplish the assigned task. Factors related to the task would be information quantity, information quality, and the ease in which the online visual presentation facilitated meaningful comparisons.

Stress

Another related state of being with regard to cognitive effort is stress. Stress is an imbalance between the environmental demands and response capabilities of the organism (Lazarus 1966). Stress may occur when environmental stimuli tax a person's coping abilities (Evans and Cohen 1987). Daily hassles can be characterized as one type of stressor, which are described as typical events that cause frustration, tension or irritation (Evans and Cohen 1987). Strain is a result of stress that may have direct effects on psycho-biological well-being (Terluin, Van Rhenen, Schauffelis, and De Hann 2004). So changes in psychological well-being from the beginning to the end of the task would suggest that the task and the information presented could contribute to cognitive stress and strain. A key implication is that it is the individual's perception of environmental demands and coping resources that determine the nature of the stress response (Evans and Cohen 1987). So if the information stimuli are perceived as exceeding one's capabilities of performing the task at hand, stress may result. These findings suggest that the longer one is exposed to (time) a perceived stressful situation, the more likely strain is to occur.

Thinking costs

Shugan (1980) suggests that there are 'costs' associated with decision-making and that the more difficult the choice (a function of the number of alternatives), the higher the 'thinking costs' associated with the decision. This would suggest that those conditions that have a higher number of alternatives should be associated with higher thinking costs. On a related note, Iselin (1993) describes the inputs used to make a decision as data load. This could include the amount of attribute information, as well as the number of alternatives presented. He suggests that the greater the data load, the greater the filtering of information by the decision-maker. Errors in the filtering process lead to lower decision quality. So Shugan focuses on the amount of information one attends to as creating greater cognitive difficulty, whereas Iselin focuses on the effort exerted in the filtering process. Quantity, load, and uncertainty are three high/low dimensions Iselin uses to operationalize task difficulty (Iselin 1993). This discussion suggests that 'thinking costs' associated with a task are a function of the task complexity and the quality and quantity of information provided to complete the assignment. Task complexity would be positively related to 'thinking costs', information quality negatively related, and information quantity may have an inverted U formed relationship.

Confusion

Related subjective measurements captured in information load studies include decision satisfaction, certainty of best decision, level of confusion while performing the task, and likelihood of not selecting the product with the greatest value (Jacoby, Speller, and Kohn 1974b). Within this set, all of them with exception of level of confusion while performing the task are outcome variables, while level of confusion describes a state during the process. Thus statements that tap into dimensions similar to confusion (e.g. complex, difficult), in addition to level of confusion, may be appropriate for testing in the scale development of cognitive effort. In a related study, subjective states were identified as either concurrent with and subsequent to the purchase decision (Jacoby, Speller, and Kohn- Berning 1974a). Level of confusion was a subjective state that was positively related to the number of alternatives and found to be negatively related to the degree of relative attractiveness of alternatives (Malhotra 1982). So again, the task complexity if operationalized as the number of choices, and the quality of information, operationalized as providing product differentiation, appear to be related to a cognitive affect state of confusion.

DECISION SATISFACTION

Decision satisfaction is defined as the degree of satisfaction with one's choice in a decision making task. Decision satisfaction has been operationalized as "How satisfied are you with your decision?" (Jacoby, Speller, and Kohn 1974). Malhotra (1982), as well as Lee and Lee (2004) have captured this outcome variable in information load experimental studies. These studies indicate that when people are overloaded they feel less satisfied. The interesting twist is that under high information load conditions, people are less satisfied with their choices, assuming they are overloaded. What if they are less satisfied because they know they did not attend to all the information (e.g. using heuristic processing) due to high information load conditions, thus they are less satisfied due to their lack of certainty in making the best decision? In this case there may be a negative relationship between cognitive effort and decision satisfaction. Why would be a consumer use cognitive shortcuts? Levels of situational involvement and enduring choice involvement may provide insight.

PRODUCT INVOLVEMENT

Involvement has been defined as a person's perceived relevance of the object based on inherent needs, values and interests (Zaichkowsky 1985). If a person has a high need or interest in an object then it is posited that he/she will be more motivated to exert processing capacity in processing information related to that object. Conversely, if a person has little or no interest in the object, then little motivation and thus attention and processing capacity may be allocated (Bettman 1979). Typical items used to measure involvement include the following semantic anchors: important/unimportant, of no concern/ of concern, irrelevant/relevant, useless/useful, means a lot to me/means nothing to me. Involvement, given its influence on processing capacity, which is posited to influence cognitive strain as an individual variable, will be examined in this study.

CHOICE INVOLVEMENT - MAXIMIZER/SATISFICER

Given the increase in product choices available in the marketplace, Schwartz (2004) suggests that this increase in options has shifted accountability of making the best product choice from the firm to the consumer. Put another way, historically if a person went to the grocery store to buy a pound of coffee, there may have been five alternatives. Given the overall lack of choice, a consumer could justify their decision outcome by saying to another or thinking to his or herself, 'well, that's all that was available, so it's not my fault if it was not the best choice.' Conversely, if a consumer goes into the store today, he/she may have a choice among 50 different coffees, factoring in brands and flavors. Under this condition, the consumer may feel greater accountability for making the 'best' choice since the options are so plentiful. Schwartz classifies people into two overarching categories. One is a Maximizer, the other is a Satisficer. A Maximizer tends to engage in more product comparisons, take longer to decide on a purchase, is more likely to experience regret after a purchase, and feel less positive about purchasing decisions (Schwartz 2004). Another way one could describe a Maximizer is that he/she may be more likely to engage in 'analysis paralysis' – analyze many options extensively to the point where he/she becomes overwhelmed and avoids making a decision. From a theoretical standpoint, a Maximizer might be classified as a systematic processor of information and a Satisficer a heuristic processor of information in a choice context (Chaiken 1980). This personality trait has had little empirical testing within the marketing domain (Schwartz et al 2002). One study suggests that Maximizers are less satisfied than Satisficers with consumer decisions and more sensitive to regret (Schwartz et al 2002). A choice outcome experiment in an online context, where retailers generally provide the greatest assortment of product information, seems well suited for testing this personality trait, positioned as an enduring trait of choice involvement (Schwartz 2004).

CHAPTER III

MODEL AND HYPOTHESES

The model tested is depicted in Figure 1. The three independent variables representing information load are product breadth, depth and density. Product breadth is operationalized as the number of alternatives, which will also be a function of the number of pages viewed. The more alternatives one has to choose from, the more pages one has to view. Product depth refers to the number of attributes for each alternative. The more attribute information available, the greater the product depth. Density is the third dimension and this is represented by the number of words per page. Specifically the more words associated with the product, the greater the information density. So in a low density situation, the attribute information may be presented in bullet points. In a high density situation, the attributes may be described in short sentences.

These three informational dimensions represent the online stimulus. The first two dimensions, breadth and density, have been studied extensively within an information processing framework, directly measuring the outcomes depicted in the response section. The third factor, density, has not been extensively studied within a website context and is typically examined using an environmental psychology framework (Stimulus-Organism-Response). This model integrates conceptualizations from information processing theory and environmental psychology. The consumer factors (organism) represent how the person perceives and evaluates the informational stimuli. Within this consumer factors section, motivational factors are examined as moderators on perceived cognitive effort. These factors are also theoretically congruent with information processing theory, since motivation plays a pivotal role in the allocation of processing capacity. Cognitive effort is posited to be a mediator between the informational stimuli and response outcomes. Choice quality is an objective response measure, determined by the weighted additive utility difference between the actual and worst choice, divided by the weighted additive utility difference between the best and worst choice (Lurie 2004). The consumer's product choice is a behavioral response reflecting choice quality based upon the alternatives available. Time spent on the task is also an objective behavioral measure, captured by the online survey software system. Time spent is posited to be indirectly a function of the amount of information processed, mediated by the perceived effort required to perform the task. Decision satisfaction is an attitude the consumer forms based upon the search and selection experience.

It is generally accepted that humans have limited processing capacity to attend to a certain amount of information at any given time (Epplis and Menger 2004). This processing limitation suggests that the greater the amount of information one has to attend to in order to complete the task, the greater the perceived cognitive effort the information presented in the task will elicit. Previous empirical studies suggest that as the number of alternatives increases, dysfunctional consequences may occur like declines in decision certainty and increases in confusion (Jacoby, Speller, and Kohn 1974; Malhotra 1982; Keller and Staelin 1987; Lee and Lee 2004). Malhotra's (1982) findings suggest that 25 or more alternatives may be a generalized point across a population where the processing capacity of people may be overloaded. Hence,

H1: Product information breadth (#alternatives) will be positively related to perceived cognitive effort with the task.

If the hypothesis is supported, then previous empirical work will be supported and theory extended in a multiple page online viewing context.

Level of motivation is positively related to processing capacity (Bettman 1979). Since Maximizers can be described as 'perfectionists' with regard to choice (Schwartz 2004), they will be more likely to have higher motivation to process all the information, thus allocating more processing capacity to the task. Under the same information load conditions, Maximizers should report lower overall cognitive effort as compared to Satisficers. At low or moderate levels of load, Maximizers may experience lower cognitive effort due to higher allocated processing capacity and because the load has not exceed the capabilities of the subject. Hence it is hypothesized that:

H1a: Product information breadth (#alternatives) will be less positively related to cognitive effort for Maximizers than Satisficers.

To test and distinguish these enduring personality traits from situational traits, product involvement will also be investigated. Higher product involvement would suggest one's motivation to attend and process the information presented would be related to one's allocation of processing capacity (Bettman 1979; Zaichkowsky 1985). Higher involvement thus may attenuate cognitive effort – up to a certain point. At high load conditions, product involvement may be positively associated with cognitive effort, however, since product involvement is associated with higher processing capacity allocation, the following hypothesis is proposed. …

H1b: Product information breadth (# alternatives) will be less positively related to perceived cognitive effort under conditions of high product involvement versus low product involvement.

An increase in the number of attributes per alternative has been empirically associated with a decrease in decision accuracy and choice quality and an increase in confusion (Helgeson and Ursic 1993; Malhotra 1982; Lee and Lee 2004). These outcomes may suggest that when the number of attributes exceeds a certain threshold, confusion and/or uncertainty with the task may increase. Therefore it is posited that…

H2: Product information depth (# attributes per alternative) will be positively related to cognitive effort.

As previously discussed, level of motivation is positively related to processing capacity (Bettman 1979). Since Maximizers can be described as 'perfectionists' with regard to choice, they will be more likely to have higher motivation to process all the information, thus allocating more processing capacity to the task. Under the same information load conditions, Maximizers should report lower overall cognitive effort as compared to Satisficers. Theoretical explanation from information processing using motivation as a key influencer of perceived cognitive effort will guide the assertion for the following hypothesis.

H2a: Product information depth (# attributes per alternative) will be less positively related to cognitive effort for Maximizers than Satisficers.

Situational involvement with the product is posited to relate positively to the processing capacity allocated to the task, thus mitigating the effects of cognitive effort (Bettman 1979). Variation in involvement is expected to correlate negatively with cognitive effort up to certain information load thresholds. Therefore the following prediction is offered.

H2b: Product information depth (# attributes per alternative) will be less positively related to cognitive effort under conditions of high product involvement.

Offline spatial density has been positively associated with perceptions of spatial crowding, which has been positively associated with negative feelings and negatively associated with shopping satisfaction (Machleit, Eroglu, and Mantel 2000). Crowding literature typically associates the density of people and/or objects with perceived ‘crowding’ responses, which may in turn elicit responses of pleasure and arousal, and manifest into approach or avoidance behaviors. If online informational crowding elicits variance in cognitive effort, then this finding will be a contribution. Online crowding, operationalized as words per page, has not been empirically tested for effects. If decreasing online crowding attenuates cognitive effort under the same information load conditions, then one practical contribution could be in online merchandising design. This result would suggest that by enhancing the ‘white space’, a reduction in cognitive effort may be achieved, which may also associate with favorable attitudes toward the website and online retailer.

H3: Product information density (# words/page) will be positively related to cognitive effort.

Within this study, density is posited to behave as an environmental stimulus as described in the Overload model. As the level of stimulus increases, it is suggested that Maximizers will be more motivated to process the information given their desire to reduce uncertainty in their decision-making (Schwartz 2004). For each attribute there will be sentences describing the attribute versus bullet points. This additional information may be perceived more positively by Maximizers than Satisficers, thus attenuating perceptions of cognitive effort. At higher loads of attribute levels cognitive overload may be more likely (Lee and Lee 2004). So although an increase in reported effort may occur between both Maximizers and Satisficers, it is posited to be greater for Satisficers.

H3a: Product information density (# words/page) will be less positively related to cognitive effort for Maximizers than Satisficers.

H3b: Product information density (# words/page) will be less positively related to cognitive effort under conditions of high product involvement versus low product involvement.

Given the cognitive processing limitations of humans to be only able to process a limited amount of information at one time, it is suggested that as the number of chunks of information (defined as the number of alternatives and the number of attributes per brand) increases, the ability of a human to process all of the information systematically will decline. Consumers may adapt by resorting to heuristic processing strategies that help them manage this overload (Payne, Bettman and Johnson 1993). This means that information may be selectively attended to, thus implying important or relevant information may be ignored. Therefore the following is suggested.

H4: Cognitive effort will be negatively associated with choice quality.

Previous empirical studies suggest that the higher the information load, the more time spent on the task, simply due to the more time it takes a person to process more information (Helgeson and Ursic 1993; Epplis and Menger 2004). If this hypothesis is not supported then discussion around processing style and how that may mediate time spent can be expatiated upon. In previous research time spent on a choice task has also been used as a proxy for cognitive effort (Garbarino and Edell 1997). So if cognitive effort and time spent are considered related, it is expected that perceived cognitive effort should be positively related time spent on the task. If cognitive effort is positively associated with information load, then this would suggest that higher cognitive effort may in a longer time to complete the evaluation and task. Thus the following hypothesis is offered.

H5: Cognitive effort will be positively related to time spent on task.

Complexity theory suggests that environmental complexity is positively associated with uncertainty. Since cognitive effort is asserted to be positively related to information load (in essence a more complex online environment), cognitive effort may also be associated with uncertainty, creating doubt in the consumer’s mind regarding one’s confidence in his/her selection.

Confidence in the product selection is posited to be positively related to decision satisfaction. Thus it is expected that the degree of uncertainty in making the best decision may be negatively related to decision satisfaction. Thus the following is predicted.

H6: Cognitive effort will be negatively related to satisfaction with product selection.

CHAPTER IV

RESEARCH DESIGN AND METHODOLOGY

EXPERIMENTAL DESIGN

The research employed a 2 x 2 x 2 between subjects experimental design. For each dimension of information load, two levels (high/low) within each dimension were tested. Presented in Figure 2 is the experimental matrix that outlines how each of the independent variables and levels will work within each of the cells.

The first dimension of information load is product information breadth, defined as the number of alternatives presented to each subject. Low and high breadth levels utilized 10 and 30 alternatives respectively. Results from a pilot test demonstrated significant perceived differences between subjects exposed to one of these two levels of alternatives. One factor determining these specific numbers is that the total number of alternatives is divisible by the number of alternatives presented on each page, so a consistent number of products are presented on each page in both experimental conditions. As the matrix in Figure 2 demonstrates, two and six pages were used, with five alternatives shown per page. Thus the total number of alternatives presented was 10 and 30 respectively.

The alternatives presented were in a matrix format, similar to the other studies discussed, with alternatives presented horizontally adjacent to each other with their respective attributes listed underneath.

The product information depth was the second manipulated independent variable. This dimension was manipulated by varying the number of attributes (5 and 15). The reason for this descriptor is because the amount of attribute information presented may be considered the informational depth presented about a product. Although the terms of breadth, depth, and density are used in retailing, these terms are operationalized slightly differently due to the independent dimensions referring to a product in an informational context. So product depth refers to the number of attributes presented for each alternative.

The third independent variable, product information density, refers to the density of information provided about each attribute. Informational density was operationalized by the words per page. The words per page can be considered an objective measure of density and pre-tests in the pilot study confirmed that subjective perceptual differences exist between low and high-density conditions. For low-density conditions, attributes were described using bullet points. For high-density conditions, attributes were described using brief descriptive sentences for each attribute. An example of each of the treatment conditions is provided in the appendix.

One picture of a product was used in the header. This picture of the product appeared on each page and was the same picture across all pages and across experimental treatments. Pictures of individual products for each cell were not used, since these graphical cues may confound the effects under investigation.

SCENARIO

Subjects were tasked with selecting a digital video camera for a person based upon this person's predetermined criteria. Subjects were randomly assigned to one of eight different treatments, as outlined in the matrix discussed previously. There was no time constraint in terms of making a decision. In addition, to enhance experimental realism, subjects could click back and forth between product comparison pages freely prior to making a final selection. The final selection page also reiterated the feature criteria and the relative importance of each feature for the choice task.

STIMULI DEVELOPMENT

The price attribute was fixed and the attribute importance on five features provided. This pre-determined attribute criterion for choice selection was used so the same objective measure for quality of choice across could be measured against all subjects. A search across several consumer electronics retailer websites helped to determine the attributes selected, with the objective of creating experimental realism (Schulz 1999). The categories and order of attributes listed on each website helped to determine the attributes chosen. For example if the online retailer offered a search option by attribute (picture quality), this feature was taken into consideration. In addition, the five attributes selected typically demonstrated different feature levels of each attribute offered among the products (e.g. pixels, LCD screen size, and weight).

For the pilot and main study an excel spreadsheet was developed, listing each attribute in a series of rows with each column representing an alternative. The values for each attribute level were assigned a numeric value (e.g. 1, 2 or 3) depending upon the attribute level exhibited (e.g. 30, 60, or 90 day warranty). Care was taken to ensure that the differences among the levels within each attribute were equivalent so that the numeric value assigned and used in the weighted added value calculation would represent an objective score beyond reproach. In addition, for those alternatives with 15 attributes displayed, two levels for each of the 10 additional attributes were employed. The first level was scored as 0, the second (higher) level scored as 1. The sum of the simple counts within each treatment were also analyzed to ensure the best choice was unequivocal if one were to argue that the presence of additional features would enhance the overall choice quality, above and beyond the levels and respective values of the five attributes provided.

The number and dispersion of attribute levels across all treatments were then evaluated to ensure consistency and homogeneity across treatments, minimizing confounding effects from effects of varying information structure (Lurie 2004). The differences in quality (calculated by the weighted added utility) between adjacent alternatives and among all alternatives within and across each treatment were evaluated to minimize task difficulty confounding effects (Keller and Staelin 1987). The average difference in quality score among each alternative within a set was kept within a limited range across all treatments.

Another broader scoped technique employed with the stimuli development was the randomization of pages within each treatment, to reduce the impact of order effects influencing one's product selection (Diehl and Zauberman 2005).

PRETESTS AND PILOT TESTS

Prior to launching the main study, paper and pencil experimental instruments were conducted with students in an undergraduate marketing class. In addition an online experimental pilot test with a convenience sample of adults was performed.

PRETEST

The purpose of the pretest was to test the appropriateness of the experimental procedure in terms of instruction comprehension, task flow, and to test the reliability of scale items proposed for key constructs (Perdue and Summers 1986). For the pretest, students in an undergraduate marketing class were used. Students were randomly assigned to one of two treatments within the context of a choice exercise, as a way of illustrating different decision making strategies employed by consumers. One treatment consisted of seven alternatives with seven features per alternative, with features described in a one-word format. The second treatment consisted of 14 alternatives with 14 features per alternative. The features in the second treatment used multiple word descriptors. Digital cameras represented the product alternatives.

Students were tasked with selecting the best product from the alternatives presented, based upon a five-feature criteria, with all features assigned equal weight. Afterwards students answered questions to describe their search and selection experience. Cognitive effort, product involvement, and choice involvement measures were tested for reliability. A sample of the questionnaire is provided in Appendix A.

The series of questions within question one represented scale items developed to measure cognitive effort. Question five represented scale items used to measure product involvement (Zaichkowsky 1985). Questions 6 through 13 represent a sample of scale items developed by Schwartz (2004) to test to what degree a person may range from being a Satisficer to a Maximizer in terms of choice involvement.

Preliminary results for the five scale items measuring cognitive effort demonstrated good reliability across the 32 subjects (α=0.894), as indicated in Table 2.

For product involvement, acceptable reliability measures were also achieved (α=0.917), as indicated in Table 3, reflecting 8 items.

For choice involvement, however, the 8 measures used did not achieve an acceptable level of reliability (α=0.548), as indicated in Table 4. As a result, additional scale items were developed for further testing prior to the main study. Also noted was that product involvement skewed toward the high end across subjects with a mean of 35 out of a possible total of 40 points. The variance of product involvement response scores was greater among women than men, but not significantly.

Subjects commented on how equally weighting the importance of each of the attributes contributed to the ease of the selection task. This was also evidenced by marks made on the paper next to attributes. Several subjects determined their final product by simply counting the number of best features across all products presented. The product with the highest number of best features was selected. Best feature is defined as the product having the highest level of a desired attribute (e.g. 30, 60, or 90 day warranty – a 90 day warranty would be considered the best). This raised the issue that the best product among the choices offered should be objectively and unequivocally superior to the other alternatives offered, regardless of the decision strategy employed. Another observation made during the task is that several subjects unstapled their two product sheets so that they could compare all alternatives at the same time. A couple of subjects commented that this strategy contributed to their ease of facilitating the task.

Based upon preliminary paper and pencil test results, several modifications were made when developing the pilot test. First, the number of alternatives was expanded to 30 items, since no significant difference in choice quality was detected between the two groups. Second the weighting across the five attributes were varied, to enhance overall task difficulty, and to potentially achieve greater variance in choice quality results.

Third, additional choice involvement scale items were developed based upon extant review of the choice and regret literature (Simonson 1992; Iyengar and Leeper 2000; Schwartz et al 2002; Schwartz 2004). These changes were implemented, in addition to developing the experiment using online software.

PILOT TEST

An online experimental instrument was developed and administered to 28 adults, ranging from 24 to 63 years of age. Ninety-six percent of subjects reported over 5 years of Internet experience. The purpose of the pilot test was threefold. One purpose was to test the online survey software for its treatment randomization capabilities. As mentioned previously, each treatment, representing either two or six pages of products (five alternatives on each page), needed to be randomized in the order presented to minimize the potential impact of order effects in the choice selection. Additionally, the treatment offered to each subject needed to be randomized. The second purpose was to test for successful manipulation checks for the information load dimensions. Since the anticipated pilot sample would be small, two extreme treatment conditions were developed for testing. One treatment represented a low breadth, low depth, and low density online product load condition. This low-low-low (LLL) treatment consisted of two pages of five alternative products per page, five attributes per product, and one-word feature descriptors. The second treatment represented a high-high-high (HHH) (breadth, depth, density) product information load condition. Thirty products (five alternatives per page across 6 pages), each with fifteen attributes, and multiple and/or full word descriptors were provided for each attribute. So the low-low-low condition presented 10 alternatives with 5 features each across two pages. The high-high-high condition presented 30 alternatives with 15 features each across 6 pages. The software was programmed to randomize the treatment presented to subjects, in addition to randomizing the order of each page within each treatment. The randomization of treatments was successfully performed across subjects.

The second purpose was to conduct manipulation checks between these two conditions, to verify significant perceptual differences existed. Successful manipulation checks were achieved across all three dimensions, as indicated in table 5.

A third purpose of the pilot was to re-test the reliability of the measures to be used in the final study. Since the subjects used in the pilot differed in terms of age and education compared to pre-tests, all measures were rechecked. Cognitive effort and product involvement both produced acceptable reliabilities (α>.80), however choice involvement across a different sample did not improve, as indicated in Table 6.

This low reliability for choice involvement suggested that additional scale items be developed and tested prior to the final main study launch.

Although the power to detect differences in cognitive effort based upon the two informational load treatments were low (0.39), differences between groups did emerge, as indicated in table 7.

Pilot tests results also suggested that cognitive effort predicted decision satisfaction. Regression analysis results suggested that cognitive effort accounted for 41% of the variance in decision satisfaction, as indicated in table 8.

In terms of time spent, there were no significant differences between treatments. This result suggested that subjects may use various strategies in making a decision. Thus an open-ended dialogue box was provided in the final survey to capture this moderator or mediator influence.

In terms of choice quality, there were many confounding factors that contributed to the subjects' choice quality. Thus measurement of choice quality and the relationship with other variables could not be asserted with credibility. The experimental instrument design, for example, did not allow subjects to click back to the page that provided the criteria for the choice, once one had started to preview the products. These design issues were addressed and resolved in the final online experimental instrument flow.

Pilot tests results also demonstrated limited variance in product involvement scores across subjects for a digital camera. Thus prior to the final experimental instrument launch, additional pre-tests were conducted across a student population using a variety of the consumer electronic items. A digital video camera demonstrated the greatest variance in terms of product involvement, with no significant gender differences.

MAIN STUDY SAMPLE

A nationwide sample of consumers participated in the online experimental task. The questionnaire contained questions that measured and tested for manipulation checks, realism checks, cognitive effort, choice quality, choice satisfaction, product involvement, choice involvement (Maximizer versus Satisfier), perceived crowding, demographics, and perceived web expertise (see appendix D for the actual experimental survey instrument).

A total of 268 consumers responded and completed the online experimental task and subsequent survey, with 49 out of 50 state residents represented (Alaska excluded).

The number of respondents from the top ten states that were represented with the respective percentage of all respondents is provided in Table 9. The number of consumers in all other states represented at least one respondent and up to five respondents.

The respondents' profiles in terms of gender, education, and online consumer electronic purchase experience are highlighted in Table 10. Females represented 59.8% of the respondents, men 40.2%. Over 80% of respondents reported having some college education or higher. This educational sample profile aligns with recent U.S. statistics indicating that 84% of Internet users have some college education (Madden 2006).

To explore if gender was a factor influencing results, given that 60% of the respondents were women, independent t-tests were performed across a variety of factors. Choice involvement, product involvement, education level, perceived experimental realism, time spent on the Internet, and Internet shopping frequency were factors tested. Only two factors, product involvement and time spent on the Internet, were significantly different. Women reported higher product involvement for digital video cameras and men reported spending more time on the Internet.

In terms of age, 50% of respondents were between 18-35, with the remaining 50% were between the ages of 36-82. Thirty-five percent were 30 years old or younger; the next thirty-five percent of respondents were between 31-45 years of age. The remaining subjects (approximately 30%) were between the ages of 46-82, with only 10% of respondents reporting being over 59. U.S. Internet users tend to index younger with over 80% of 18-29 and 30-49 year olds reporting being Internet users, as compared to just

33% of those adults older than 65 (Madden 2006). Additionally statistics indicate that 18-29 year olds go online more so than any other age group (88%) (Madden 2006).

In terms of online consumer electronic purchase experience, 54% of respondents reported having purchased a consumer electronic product online, with 42% reporting owning a video camera. Forty-six percent of men reported owning a video camera and 39% of women made this claim. Men also slightly over-indexed compared to women in terms of consumer electronic purchase experience online (62.6% versus 48.4% respectively).

Ninety-four percent of the respondents (N=252) reported the number of years they recalled using the Internet. Ninety-five percent reported within a range of 1-15 years; the most popular response being 10 years. The actual range varied from 1-28 years. The distribution is reported in the table 11. The overall majority reported within a range of 7-15 years using the Internet.

CHAPTER V

DATA ANALYSIS AND RESULTS

NON-RESPONSE BIAS

An online panel of consumers was recruited to participate in the online experimental treatment. Web-based access panels are pools of subjects who have expressed their willingness to participate in Web surveys on a regular basis (Bosnjak, Tuten, and Wittman 2005). Of the 359 respondents who opened the invitation, 263 completed the experimental task and answered the post-test questions, yielding a 73% response rate. This relatively high response and completion rate compared to other online response rates reported (Roster, Rogers, Hozier, Baker, and Albaum 2007) may be attributed to several factors. First, subjects were offered an incentive, thus the expected rewards may have outweighed the expected ‘costs’ for many (Dillman 2007). Second, the context involved online shopping, an activity common to many Internet users (Madden 2004). Third, factors determining consumer recruitment may have included interest and/or experience in consumer electronics. Maximizing the participation from selected subjects is considered particularly effective because this approach attempts to eliminate nonresponse bias entirely (Yu and Cooper 1983).

The experimental instrument responses were collected over a six-day period. Over 50% of the responses were recorded the first day the online experimental instrument launched. To test for early versus late response bias, subjects were divided into two groups; first day responders and second to sixth day responders. Several factors were analyzed to determine early versus late response bias; age, education level, years of experience using the web, gender, time spent in the experimental task, and total time answering the survey questions. For all these factors, there were no significant differences between the subjects who responded on the first day versus those who responded later in the week. Hence, it was concluded that there was no nonresponse bias.

REALISM CHECK

An online search for digital video cameras in the $300-$450 price range yielded a range from 11 to 25 alternatives available from various large online retailers (Best Buy, Circuit City, Wal-Mart). So the scenario, while using objective choice criteria to create internal validity, was designed to exhibit experimental realism since the task reflected the breadth and depth of information shoppers would face when searching for a digital video camera online (Schulz 1999). To test the face validity of this experimental design, an experimental realism scale was used to assess the realism of this experiment across all respondents. After completing the assigned task, subjects rated on a five point scale 'how realistic do you think the product information presented reflects what you would expect to see when searching for this type of product online?" A score of one represented 'not realistic at all' to a score of five meaning 'completely realistic'. The mean for all 268 subjects was 3.5 with a mode of 4.0. Only 15% of respondents reported a response indicating the information presented was not realistic. There were no significant differences in experimental realism among the eight different treatment groups. Interestingly subjects in the high breadth condition (30 product alternatives) perceived the information as being less realistic (means ranging from 3.2-3.4) compared to the subjects in the low breadth conditions (10 product alternatives), even though there was no statistical significance in the differences. Prior to selecting a digital video camera as the experimental product, an online search for digital video cameras on two large online consumer electronic retailers' websites (Best Buy and Circuit City) indicated an assortment ranging from 19-23 camcorders within a particular price range. Although a slightly higher realism mean score was achieved in a pilot test, a digital camera was used. One possible explanation may be that the assortment of digital cameras online is deeper than that of digital camcorders, and consumers may be aware of these differences.

When examining the realism responses between those subjects who own a video camera and those who don't, some interesting trends emerge. As stated previously, 41.8% (n=112) of subjects reported owning a video camera. Sixty-three percent of these consumers scored the information presented as being somewhat to completely realistic, compared to 54.9% of those who reported not owning a digital video camera. So those who have experience acquiring this type of consumer electronic item reported higher realism than those who have not acquired this type of product. Although there were no significant statistical differences between these two groups, significant differences did emerge between those subjects who have purchased a consumer electronic item online versus those who have not (p=.001). Over 66% of respondents who have purchased a consumer electronics item online reported the information presented as being somewhat to completely realistic, as compared to 41.5% of those who reported never purchasing a consumer electronic item online. Thus even though the overall realism scores are not as high as experienced in the pilot test, the realism scores are more positive with those subjects who have experience with the actual consumer electronic item and/or purchasing a consumer electronic item online. These different expectations based upon prior experience may have marketing implications. One is that for consumers shopping for the first time online for a consumer electronics item, the initial assortment may be larger than what is anticipated. How the consumer will respond and adapt to this condition may have significant marketing implications, some of what may be uncovered and discussed later in this research.

MANIPULATION CHECKS

There were three individual and one overall manipulation check performed. The three individual manipulation checks tested for significant differences perceived by subjects on the information's breadth (number of alternative products), depth (number of features per product provided), and density (number of words and consequently affecting the amount of space per page). The fourth manipulation check asked subjects to rate the overall amount of information they perceived to be provided during the task.

For each individual manipulation check, two slightly different questions were asked. For breadth and depth, subjects were asked to rate on a five-point scale if there were 'too few' to 'too many' products or features presented and if the number of products or features presented were 'insufficient' to 'overwhelming.' The first statement attempted to capture the respondents' cognitive perception of the amount of information presented. The second statement attempted to capture the emotional response elicited from processing the information.

Breadth

As seen in table 12, the breadth manipulation check demonstrated significant differences between the high and low breadth conditions for both statements ($p=.000$). The high breadth condition presented 30 alternatives over six pages, whereas the low breadth condition presented 10 alternatives over two pages. The number of alternatives per page was held constant.

Depth

Significant perceptual differences between subjects exposed to the high depth (15 features per product) versus the low depth condition (five features) were also reported (p=.000) for both questions. These results are highlighted in table 13.

Density

For the density manipulation check, however, no significant differences were detected between the low and high condition. As indicated in table 14, the mean scores and variances were both groups were almost identical.

Given the low variance between groups, the statistical power to detect differences was diminished as well (Cook and Campbell 1979). Reflecting back upon the stimuli, the most significant perceptual difference in terms of space on each page seemed to be demonstrated in those conditions where each product had 15 features. Spacing differences did not appear significant when looking at a page that contained only five features, even with the words written out. Additional tests were performed to see if *perceptual crowding* differences existed between subjects who were exposed to different depth conditions. *Results confirmed significant differences (p=.004) in total perceived crowding scores between low and high depth conditions, as demonstrated in table 15.*

Analysis, as indicated in table 16, excluded breadth as a variable because this measure captured perceptual information load across pages, not within a page. *So a perceptual crowding manipulation was successfully executed but only between those subjects who experienced variance in depth of features presented (p=.004).*

Overall perceived information load

Respondents perception of the overall amount of information load based upon the three factors of breadth, depth, and density was significant (p=.000). As table 17 results indicate, product depth appears to be the most powerful driver, followed by partial support for density (p=0.054), and then breadth (p=.093). It should be noted, however, that the observed power for density and breadth was not as strong as it was for depth.

As the table 18 demonstrates, the overall perception of information load increases as expected from a low breadth, depth, and density condition to the high treatment conditions across all three dimensions. The mean scores progress from a low score of 4.0 to a high score of 5.17, representing the highest objective and perceptive load condition

RELIABILITY OF MEASURES

Perceived web expertise

Respondents were asked to evaluate themselves on four tasks or activities performed on the web. The four items represented perceived web expertise, which has demonstrated good reliability in previous studies (Yaveroglu 2002). Among these subjects, good reliability for this measure was also achieved ($\alpha = 0.911$), indicated in table 19. Table 20 shows the questions representing the scale. Although the scale demonstrated good reliability, the variance around each of the items was limited. This limited variance may suppress the power of this measure to act as a covariate in later analysis, if needed (Cohen, Cohen, Aiken and West 2003).

Given the wide age range of respondents, correlation analysis was performed to see how perceived web expertise, age, and years of Internet use may relate. As one might suspect there was a positive and significant relationship between age and years of Internet use (.169, p=.007). In addition there was a stronger relationship between perceived web expertise and years of Internet use (.271, p=.000). There was no significant relationship, however, between age and perceived web expertise. This result suggests that younger adults may perceive themselves to be more proficient on the web than their older counterparts.

Product Involvement

Given that younger consumers tend to be highly involved with technology (Burns 2006d), their involvement with consumer electronic products may also be higher than the general population. Thus greater variance among a more diversely aged population would be expected. The scale items used were originally developed by Zaichkowsky (1985). The seven point scale produced a reliability score of 0.968 (table 21). The means and variance associated with the overall product involvement scores indicates some range and the differences between men and women were significant (p=.022).

In this sample, women demonstrated greater product involvement and slightly less overall variance than men (table 22). Overall a subject responding to the 7 item, five point scale could produce a score ranging from 7 to 35, 35 indicating the highest product involvement score. An overall mean of 26.56 points suggests that the subjects had an average response of a 5 on each of the five items, indicating some positive level of involvement with digital video cameras.

Choice Involvement - Maximizers and Satisficers

Several scale items originally developed by Schwartz (2002, 2004), in addition to four items developed for this study were used to measure enduring choice involvement. Pilot test scale items used previously produced low reliability. Additionally factor analysis suggested three different factors emerged from these scale items. As a result, additional scale items were developed that focused on product choice contexts and how regret in making a poor choice may drive effort. Schwartz's scale items focus on global contexts (shopping, listening to the radio, choosing a partner), whereas the additional scale items added focused on product choice contexts.

Results from reliability and factor analysis (see tables 23 to 25) suggest that four items of the 11 tested correlate and load positively with each other.

These choice involvement scale items attempt to uncover the motivations behind the decision process. Those subjects who are more likely to seek all possibilities or options available because they are motivated to the make the best choice, establish high standards for themselves and want to avoid feeling the regret of making a bad decision are posited to be drivers of high choice involvement. Schwartz suggests that people who demonstrate high choice involvement are likely to engage in 'analysis paralysis.' One marketing implication is that a consumer exposed to a large product assortment, may defer making a buying decision due to the uncertainty of the outcome (Iyengar and Leeper 2000).

Although the reliability analysis of the full set of questions yielded what could be considered an acceptable score (α=0.73), factor analysis suggested three different components being extracted from the set of questions. These three factors contributed to

53% of the explained variance. Conversely, when the final four items were loaded for factor analysis, only one component was extracted (table 26). This factor accounted for over 59% of the variance, as demonstrated in table 27. Thus these four scale items were used in the analyses for choice involvement for the applicable hypotheses.

Cognitive Effort

Five items on a seven-point scale comprised the construct, ‘perceived cognitive effort with the task’. Analyses from 268 subjects’ responses yield a reliability coefficient of 0.952 (table 28). Subjects were asked to describe their search and selection experience on a seven point scale, reporting varying degrees of difficulty from ‘extremely difficult’ (scored a 7) to ‘extremely easy’ (scored a 1). The ability to evaluate product features, distinguish product differences, compare products, process features offered, and select the best product were items asked. These reflective indicators of cognitive effort and their relationship with each other are displayed in table 29. As indicated in table 29, reflective indicators of a latent construct are internally consistent and equally valid, so that if an indicator is removed, the construct validity generally remains unchanged (Jarvis, Mackenzie, and Podsadoff 2003). Given that the indicators do share a common theme and that the measures are posited to have the same antecedents and consequences, lends support for the items to be considered reflective versus formative.

Choice quality

Choice quality was calculated using a mathematical formula that is derived from the weighted added values (WAV) of the product chosen and those of the best and worst weighted added value scores (Lurie 2004). Specifically the formula calculated as follows:

Choice Quality = $(WAV_{chosen} – WAV_{worst})/(WAV_{best} - WAV_{worst})$

The range in scores would vary from a low of zero to a high score of one if the best choice is chosen. An ANOVA was initially run to see how the choice quality scores varied between different experimental treatments. The overall means for each of the treatments is shown in table 30.

There were significant overall differences on choice quality (p=.001) based upon information load treatments, as seen in table 31 The assumption with choice quality is that the best choice utilizes compensatory process and utilizes all the information presented. Although this may not be considered realistic, this has been the practice (Eppler and Mengis 2004; Lurie 2004; Lee and Lee 2004; Lurie 1999; Malhotra 1982). Significant differences in choice quality will be examined between each of the cells. Also, the information captured would also allow the researcher to capture what has been called 'satisficing' choices (Malhotra 1982), choices that are scored highly (e.g. 0.88-.0.94), although not perfect (1.0). Cognitive effort will then be added as an independent variable to test for mediation effects (Baron and Kenny 1986). Tests for significance and variance accounted for can be analyzed among the different regression equations.

Time Spent

The second dependent variable, time spent, represents the time from when the first page of product information was viewed to when the final product choice was made. The online survey software captured this information, so the time recorded is the actual total time spent versus a self-reported time. The total time is measured in terms of seconds. It is expected that time spent will be positively related to product information load. Previous research suggests that the more complex the information, the more time it takes a person to reach a decision (Helgeson and Ursic 1993).

Overall significant differences in time spent on the task existed among the different treatment groups ($F=3.453$, $p=.001$). Post hoc analysis showed significant differences in total time spent between those conditions that varied in terms of breadth and depth. A regression analysis using the three dimensions of information load regressed on time spent yields an overall significant result ($F=7.3$, $p=.000$), with breadth and depth yielding positive and significant beta coefficients ($\beta=0.22$, $p=.000$, $\beta=.160$, $p=.008$) respectively.

Time spent on a choice task has also been used as a proxy for cognitive effort (Garbarino and Edell 1997). Whether this relationship will be linear across the ranges tested has yet to be determined. The results can be plotted to see the type of relationship that may exist and then run the appropriate statistical analysis (e.g. regression with time as the dependent variable) for curvilinear effects.

Satisfaction with Decision

For satisfaction with decision, a seven point scale is used. Decision satisfaction has been operationalized as “How satisfied are you with your decision? (1 – very dissatisfied; 7 – very satisfied) (Jacoby, Speller, and Kohn 1974).

HYPOTHESES RESULTS

H1: Product information breadth (#alternatives) will be positively related to cognitive effort. SUPPORTED

An ANOVA with product breadth (high/low) as the independent variable and cognitive effort as the dependent variable was performed. As seen in table 32, a significant difference in cognitive effort between low and high product breadth conditions was obtained ($p = 0.000$) with high product depth conditions yielding higher overall cognitive effort scores. Results support a positive relationship between product information breadth and perceived cognitive effort with the search and selection task ($\beta=0.333$). Results from regression analysis suggest that the number of product alternatives contributes 10% to the variance explained in cognitive effort. Previous choice studies conducted in a computer-mediated environment typically provide all alternative information on one page. This study provided information across multiple pages. This means that subjects were not allowed to view all options at once, but were allowed to scroll back and forth between pages.

In earlier paper and pencil pre-tests, the researcher observed subjects unstapling the sheets of product information so they could view all products side by side. In addition, the product sheets collected, post the task in these pre-tests, frequently had crossed-out marks on products and feature attributes as a means of eliminating and not attending to pieces of information deemed irrelevant. So although the results are not surprising, the significant relationship between product breadth and perceived cognitive effort with the task contributes to the body of knowledge in this area. How the channel context (offline versus online), given the same product breadth may influence perceived cognitive effort with the search and selection task may be theoretically as well as managerially insightful for future study.

H1a: Product information breadth (#alternatives) will be less positively related to cognitive effort for Maximizers than Satisficers. NOT SUPPORTED

Respondents were scored on a choice involvement continuum scale where a person with a high score may be described as a Maximizer and a person with a low score, described as a Satisficer. A higher choice involvement score would suggest that a person may be more of a Maximizer when making a decision among various products offered as compared to others with a lower choice involvement score. A relatively lower score would suggest a person may be lower on choice involvement, thus more likely to engage 'satisficing' decision strategies when making a decision.

Regression analysis was performed, coding the breadth conditions -1, +1 for low and high respectively, and using centered choice involvement scores to test for interaction effects (Cohen, Cohen, West, and Aiken 2003). To maximize the statistical power to detect significant interaction effects, McClelland and Judd (1993) recommend coding categorical treatments in this manner so the product of the two variables will yield a greater range of information, as compared to dummy coding for example.

As indicated in Table 33, there were no significant interaction effects between choice involvement and product breadth, thus choice involvement does not appear to moderate product breadth, in terms of cognitive effort. Choice involvement, however, does exert a significant negative main effect on cognitive effort ($p=.017$). The negative beta coefficient for the centered choice involvement score indicates that those subjects who scored above the average for choice involvement (Maximizers) reported an overall lower cognitive effort score, compared to those who scored below average on choice involvement (Satisficers). This result suggests that the higher one's choice involvement, the lower one's perceived cognitive effort with the task. The first-order coefficients in regression equations containing interaction terms represent the regression of Y on each predictor at the value of zero on the other predictor (Cohen et al 2003). So a value of 0 for the breadth condition would represent a medium breadth condition, given that low and high conditions were coded as -1 and +1 respectively.

This result supports information process theory, given that Maximizers are more highly involved in the choice process, thus allocating more processing capacity to the task. Allocating more processing capacity would suggest the subject perceives less effort performing the task. To the researcher's knowledge, choice involvement tested within a computer mediated environment, has not been empirically tested to date. Thus the construct and the context together, help to extend and provide additional support to the information processing theory of consumer choice.

H1b: Product information breadth (# alternatives) will be less positively related to cognitive effort under conditions of high product involvement. NOT SUPPORTED

Regression analyses, similarly to what was performed for H1a, was conducted using breadth with product involvement substituted for choice involvement. As seen in table 28, product involvement exerted a significant negative effect on cognitive effort, but the interaction between breadth and product involvement was not statistically significant (p=.575). Thus product involvement does not moderate product breadth, but operates as a main effect on cognitive effort. The negative beta coefficient for the centered product involvement score indicates that those subjects who scored above the average for product involvement reported an overall lower cognitive effort score. The first-order coefficients in regression equations containing interaction terms represent the regression of Y on each predictor at the value of zero on the other predictor (Cohen et al 2003). So a value of 0 for the breadth condition would represent a medium breadth condition, given that low and high conditions were coded as -1 and +1 respectively.

H2: Product information depth (# attributes per alternative) will be positively related to cognitive effort. SUPPORTED

A regression was performed with the dummy coded variables of low and high product information depth (0/1), regressed on cognitive effort. As seen in table 35 the hypothesis was supported given the positive value of the beta coefficient for depth and being statistically significant (β=0.150, p=.014), however it should be noted that the impact on cognitive effort was minor, accounting for less than two percent of the variance.

Reflecting upon the assigned task, product information depth's relatively low impact on cognitive effort is not surprising. The task assigned is to select the best product, thus the product features may help to distinguish desirable products from less desirable alternatives. In half the treatment conditions, subjects were provided with five feature attributes, all which were relevant to the choice assignment. Thus the quality of information in these treatments may have been considered high by the subjects. Quality of information has been operationalized as the ratio of relevant to non-relevant information provided (Keller and Staelin 1987). When information load is held constant and quality of information increased, decision effectiveness improves (Keller and Staelin 1987). Thus the attribute information may have to a certain point mitigated perceived cognitive effort because the information was helpful in distinguishing and selecting the best alternative.

Although the result may not be surprising, it does help to put the information load debate in a new perspective. Previous debates centered upon which information load dimension is more influential in terms of objective choice quality– features or number of alternatives (Lee and Lee 2004). This research shifts the perspective to examine how the information influences consumers' cognitive states while proceeding through the search and selection task. This result suggests that attribute information requires effort (thinking costs) but the benefits of the information (value) may offset the costs in terms of the task at hand, thus the lower overall influence on cognitive effort. Given that the necessary information to make the best decision was provided in all treatments, comparing this information across the number of alternatives may be the key driver of effort required to perform the task well within this context.

H2a: Product information depth (# attributes per alternative) will be less positively related to cognitive effort for Maximizers than Satisficers. NOT SUPPORTED

A regression analysis, similar to that performed for H1a, was performed (replacing breadth by depth). As seen in table 36, there are no significant interaction effects detected between product depth and choice involvement. This result suggests that choice involvement does not moderate product depth. The model does suggest, however, that choice involvement does exert a negative main effect on cognitive effort. The choice involvement scores are centered, thus those subjects who score above the average on choice involvement (Maximizers), are predicted to score lower on cognitive effort, compared to those who score lower on the choice involvement scale (Satisficers). Satisficers would report a negative centered score, thus the product of two negative scores would yield a positive number – adding to the cognitive effort score.

This result supports information processing theory in that choice involvement mitigates perceived cognitive effort when examining product attribute information in an online context. An extension of this work may be to explore processing strategy differences between Maximizers and Satisficers, taking into account the amount of information absorbed during similar shopping tasks. Since attribute information enables product differentiation, the decision strategy differences Maximizers and Satisficers may be employ may provide theoretical, as well as managerial insights in terms of merchandising and promotion.

H2b: Product information depth (# attributes per alternative) will be less positively related to cognitive effort under conditions of high product involvement. NOT SUPPORTED

A regression analysis was performed, similarly as outlined in H2a, substituting a centered product involvement for choice involvement and the respective interactive product between depth and product involvement. Results, as outlined in table 37, indicate that even though the overall model is significant (p=.000), the interaction between product depth (attributes) and product involvement is not statistically significant. Therefore, results suggest product involvement does not moderate the cognitive effort associated with viewing product attribute information. What the results do suggest, however, is that product involvement exerts a negative main effect on cognitive effort (p=.000). Thus, subjects who scored above average in product involvement were more likely to report lower perceived cognitive effort associated with the task, as compared to those who scored below average on product involvement. As previously noted, the product involvement score is centered, thus a person with a below average product involvement score would be scored negatively. The product of two negative scores is a positive output. According to the regression model, below average product involvement would contribute positively to the cognitive effort score.

H3: Product information density (# words/page) will be positively related to cognitive effort. NOT SUPPORTED with full sample.

An ANOVA was run with density as the independent variables and cognitive effort as the dependent variable. As indicated in table 38, density did not have a statistically significant positive relationship on cognitive effort. This is understandable given that the manipulation checks were not significant between treatments for the varying density conditions. In previous studies measuring density, density itself does not elicit variance in responses but rather the subjects' perception of crowding based upon what they experienced (Eroglu and Machleit 1990; Hui and Bateson 1991). Eroglu and Machleit's (1990) simulation study suggests high retail density (brick and mortar context) is positively associated with perceptions of retail crowding, particularly accentuated under goal oriented task conditions. Hui and Bateson (1991) found that consumer density directly and positively influenced perceptions of crowding. Hence two additional hypotheses (H3 1 and H3 2) were tested.

H3 1: Product information density, for those subjects who perceived crowding, will be positively related to cognitive effort. NOT SUPPORTED with manipulated sub-sample.

Next analysis was conducted using only those subjects who were manipulated, meaning they perceived the pages of information to be crowded (a score greater than three on a five point scale). The crowding manipulation check scores were regressed on cognitive effort. From an original sample size of 268, 112 subjects reported experiencing some form of density manipulation. These subjects skewed toward experiencing a 'crowded' effect, with a mean score of 4.11 on a five point scale ranging from one indicating a perception of the page being 'spacious' to a score of five, indicating the information on each page appeared 'crowded'. As seen in Table 39, the manipulated sample also revealed no significant differences of density on perceived cognitive effort with the task.

So with the full sample, H3 was not supported. With a subset of respondents who did experience the manipulated effect, density for H3 1 was also not supported. Based upon previous studies that suggest perceptions of crowding elicit perceptual responses (Eroglu and Machleit 1990; Hui and Bateson 1991), a second alternative hypothesis was developed and tested.

H3 2: Perceived crowding will be positively related to cognitive effort. SUPPORTED

With the full sample (n=268), perceived crowding was regressed on cognitive effort (Table 40). The positive standardized beta coefficient (β=.336, p=.000) accounted for a little over 10% of the total variance. Thus a modified version of H3 is supported (H3 2), substituting perceived crowding for density.

This result, although not originally posited, contributes to the theoretical testing of perceived crowding in an online, multiple page context, using informational properties as the stimuli. As discussed previously, crowding has been operationalized in online contexts, primarily between websites and capturing approach and avoidance behavioral responses. This finding extends not only the contextual application of environmental crowding, but how online environmental variables may influence cognitive states. Given perceived crowding impacts perceived cognitive effort positively, future studies exploring online design factors that may contribute to perceptions of crowding may be beneficial. If certain website design factors elicit perceptions of crowding, then design alterations can be made to reduce the associated cognitive effort. If cognitive effort is positively associated with website ease of use, then such modifications may increase consumers' likelihood to return (Venkatesh and Davis 2000).

H3a: Product information density (# words/page) will be less positively related to cognitive effort for Maximizers than Satisficers. NOT SUPPORTED

Regression analysis was performed coding low and high density conditions as -1/+1 respectively, along with centered choice involvement scores as first order independent variables. The respective product of these two variables formed the interaction variable to test for moderation (Baron and Kenny 1986). As indicated in table 41, choice involvement does not moderate the effects of density on cognitive effort, but does exert a significant main effect (p=.002)

This result is understandable given that density did not have main effect on cognitive effort in previous analysis reported. The overall model was significant, as indicated in table 42, however, the variance within choice involvement appears to be driving the overall significant results.

H3a 1: Product information density, for those subjects who perceived crowding, will be less positively related to cognitive effort for Maximizers than Satisficers. NOT SUPPORTED

Regression analysis with the manipulated sub-sample (N=103) did not produce significant results for the overall model, as indicated in table 43.

H3a 2: Perceived crowding will be less positively related to cognitive effort for Maximizers than Satisficers. NOT SUPPORTED.

Regression analysis was performed in a similar manner as outlined in H1a. Perceived crowding and choice involvement were independent variables analyzed, along with the respective interaction term, with cognitive effort as the dependent variable. Although the overall model was significant (p=.000), the interaction term for both first order variables was not significant (p=0.588) as indicated in table 44. These results suggest that choice involvement does not moderate the effects of perceived crowding on cognitive effort, but exerts a direct negative influence. Thus, those subjects who scored above average on the choice involvement scale (Maximizers) overall would be likely to report lower cognitive effort scores as compared to those subjects who scored lower than average on choice involvement.

These results extend previous research in two ways. First, perceived crowding and choice involvement are empirically tested together and demonstrate significant effects in an online choice context. Secondly, both constructs empirically demonstrate an effect on cognitive effort. To the researcher's knowledge, these three variables (cognitive effort, perceived crowding, and choice involvement) have not been empirically tested together in an offline or an online context. These latter two variables, within this particular sample, accounted for approximately 13% of variance of cognitive effort.

H3b: Product information density (# words/page) will be less positively related to cognitive effort for those with high product involvement. NOT SUPPORTED

Regression analysis was performed coding low and high density conditions as -1/+1 respectively, along with centered product involvement scores as first order independent variables. The respective product of these two variables formed the interaction variable to test for moderation (Baron and Kenny 1986). As indicated in table 45, product involvement does not moderate the effects of density on cognitive effort, but does exert a significant main effect (p=000.)

This result is understandable given that density did not have main effect on cognitive effort in previous analysis reported. The overall model was significant (p=.000), however, product involvement appears to be driving the overall significant results. The negative beta coefficients associated with product involvement do suggest that a person with an above average product involvement, is predicted to experience overall less cognitive effort, than a person with below average product involvement.

H3b 1: Product information density (# words/page), for those who perceived crowding effects, will be less positively related to cognitive effort under conditions of high product involvement. NOT SUPPORTED

Similarly to the steps outlined in H3b, a regression analysis was performed with a manipulated sub-sample of respondents who perceived crowding. Density and product involvement, along with their product term, were analyzed to test for effects on cognitive effort. As indicated in table 46, product involvement does not moderate density (p=.816) for the manipulated sub-sample of respondents who perceived crowding. The overall model was significant (p=.011), however this is attributed to the main effects of product involvement on cognitive effort (p=.004).

H3b 2: Perceived crowding will be less positively related to cognitive effort under conditions of high product involvement. NOT SUPPORTED

Since the perception of crowding does have a positive effect on cognitive effort, the impact of product involvement and the perceptions of crowding on cognitive effort were analyzed. Perceptions of crowding and product involvement, along with the interaction term of both, were independent variables and cognitive effort was the dependent variable. The results presented in table 47 suggest that product involvement does not moderate perceptions of crowding, but acts as a significant main effect. The overall model was significant, attributed to the significant positive effect of crowding and the negative main effect of product involvement on cognitive effort. This model accounted for 18.6% of the variance in cognitive effort.

These results suggest that perceived crowded informational conditions positively contributes to the cognitive effort in an online search and selection task. In addition, a person who is highly involved in the product category may not perceive an effortful search and selection process as compared to another consumer who is not as involved in the product category. These results align with previous findings that suggest the task orientation (goal/experiential) of the user may moderate perceptions of perceived website complexity (Nadkarni and Gupta 2004). A person with high product involvement may be more likely to be goal-oriented (e.g. purpose of acquiring knowledge), as compared to an experiential user who may be just browsing for entertainment.

H4: Cognitive effort will be negatively associated with choice quality

SUPPORTED

Choice quality was regressed on cognitive effort. Choice quality was measured as the weighted additive value (WAV) of the product chosen minus the weighted additive value of the worst choice available, divided by the difference between the WAV best and WAV worst choice. Results suggest (table 48) perceived cognitive effort with the task is negatively associated with choice quality ($\beta=-.239$, $p=.000$). Although the hypothesis is supported, it should be noted that cognitive effort only accounted for less than 6% of variance in choice quality.

This result may be considered significant for two reasons. First, a perceived individual state empirically demonstrates influence on choice quality. Typically objectively measured informational factors have been manipulated to test for choice quality differences. This research attempts to test for a mediation variable that may also predict the quality of choice outcomes. Although the variance accounted for is minimal, this study may open the research door for future studies to explore other factors that may mediate objective informational properties influence on choice outcomes.

H5: Cognitive effort will be positively related to time spent on task.

NOT SUPPORTED

Time spent on task was regressed on cognitive effort (table 49). This relationship was not statistically significant. This result is interesting because in previous studies, time spent on task has been used as a proxy for 'cognitive effort' (Garbarino and Edell 1997). Stated differently, if a person spent more time performing a task, the assumption was that he or she was exerting more effort. These results suggest no direct relationship.

Given this result, an alternative explanation may be that subjects adapt to their information environment by using different decision strategies, thus attenuating time spent with high loads of information (Payne, Bettman, and Johnson 1993). Variance in decision strategies could be driven by a variety of factors. One factor could be the subject's seriousness of the task. Since there were no incentives for selecting the best product, only an incentive for finishing the survey (online panel incentive points for completing the survey), respondents may have rushed through the task, more interested in finishing rather than making the best selection. In addition there was no feedback mechanism incorporated into the survey to tell the subject how well he/she actually performed based upon the criteria provided. Another explanation may be that since the product selection was not a real purchase with risk implications, the task was not given serious consideration. Thus time spent on the task for many respondents may have been moderated by this less than serious consideration for the assigned task. Another observation was noted when investigating those subjects who made poor choice decisions. Several subjects commented that they became overwhelmed and finally just picked one product. This would suggest that negative feelings may have propelled the subjects to end the task prematurely, to avoid prolonging these feelings. These alternative explanations, although not empirically measured and tested in this study, suggest that there may several factors that may moderate the time spent on the task. Given that time is a measure firms do capture when examining online behavior, future studies that examine potential moderators and mediators to time spent on the task may be beneficial.

H6: Cognitive effort will be negatively related to satisfaction with product selection. SUPPORTED

A regression analysis was performed with cognitive effort as the independent variable and choice satisfaction as the dependent variable. Regression analysis results in table 50 suggest that cognitive effort accounts for almost 30% of the variance in choice satisfaction. The standardized beta coefficient for cognitive effort was negative and significant (β= -.544, p=000).

This result suggests that consumers may be more satisfied with their choice, when the selection process is not effortful. Decisions that require effort may be perceived as difficult, creating doubt in the mind of a consumer, thus attenuating one's confidence of making a good choice. Choice confidence and choice satisfaction were strongly correlated within this sample (0.772, p=.000), with subjects reporting a lower choice confidence mean (4.78), compared to choice satisfaction (5.04). Since Maximizers exerted overall less cognitive effort than Satisficers, this would suggest that Maximizers may be more satisfied with their product selection than Satisficers. Comparing the choice satisfaction means between both groups yielded significant differences (p=.000), with Maximizers reporting a mean score of 5.34 compared to Satisficers with a mean satisfaction score of 4.72.

POST HOC ANALYSIS

Cognitive Effort as a Mediator

Although not hypothesized, the test for mediation using cognitive effort was performed. Regression analyses were performed as outlined in previous research to test for mediation (Baron and Kenny 1986). First, three information load factors, breadth, depth, and perceived crowding, were regressed on choice quality. Since perceived crowding had an impact on cognitive effort, not density, this dimension was used as the third information variable. The overall model was significant (table 51), however depth as an individual factor was not statistically significant (p=.463). Breadth (β = -.259, p=.000) and crowding (β= -.123, p=.044) had a negative relationship to cognitive effort (table 52).

As indicated earlier, cognitive effort also had a significant relationship with choice quality (β = -.333, p=.000). Next all three factors, breadth, crowding and cognitive effort were regressed on choice quality. Depth was not included because there was no relationship with choice quality and a relationship between depth and cognitive effort had already been established (see H2). The overall model, as indicated in table 53, was significant (p=.000), accounting for approximately 9.5% variance in choice quality. Upon closer inspection of the actual model, as illustrated in table 54, breadth and cognitive effort remained significant, but with both beta coefficients diminishing. Crowding became insignificant. These results suggest that breadth and cognitive effort both act as independent factors related to choice quality (see table 55), noting also that breadth demonstrated a significant positive relationship with cognitive effort (table 32). When cognitive effort and breadth are analyzed on choice quality (table 56), both exert a significant negative effect.

According to Baron and Kenny (1986), in order for cognitive effort to mediate the relationship between breadth and choice quality, the relationship between breadth and choice quality should become insignificant when cognitive effort is inserted into the regression model. The results in table 50 suggest otherwise. Results suggest that both breadth and cognitive effort both exert a direct influence and also may covary. Conversely, product information depth, individually, was not significantly related to choice quality, but was statistically significantly related with cognitive effort (table 57). So although cognitive effort may not mediate product breadth, these results suggest that cognitive effort may mediate between product depth and choice quality, given that when cognitive effort is added to the regression equation, the overall model is significant (p=.000) but depth is insignificant and cognitive effort remains significant (table 58).

SUMMARY OF RESULTS

Table 59 summarizes the results of the hypotheses proposed and tested. Figure 3 models the empirically supported relationships among the variables and constructs tested.

Product information breadth and depth both influenced perceived cognitive effort in a positive manner. Product information density had no effect on cognitive effort, but did influence perceived crowding, which in turn positively influenced cognitive effort.

Product and choice involvement did not moderate the relationship between the three product informational dimensions and cognitive effort. Results suggest that product and choice involvement exerted a direct negative effect on perceived cognitive effort with the task.

Cognitive effort exerted a negative influence on choice quality and decision satisfaction. There was no significant relationship between cognitive effort and time spent on the task.

DISCUSSION OF RESULTS

Results from this empirical study warrant several areas of discussion. First, in terms of decision making contexts and choice quality the following comments are offered. Within a multiple page online context, breadth of products made a more significant impact on choice quality than the other dimensions tested. Although this may not be surprising given that more products increase the odds of making a poor choice (Malhotra 1982), it should be noted that depth had no impact on choice quality. This departs from previous studies (Lee and Lee 2004) conducted in an online context. One could argue that given the quasi -experiment, the actual quality of decisions in a real purchase situation may improve, and hence the task did not mirror reality. Given that a percentage of subjects in all but two groups did select the best product counters this argument. In addition it should be noted that time was not limited in the task assigned. Previous experiments typically give subjects only a limited amount of time, to induce stress and potential overload (Lurie 2004; Lee and Lee 2004; Suri, Long, and Monroe 2003). This study, although employing experimental treatments, attempted to simulate a typical online search and selection process a consumer may experience when looking for a consumer electronics product. Subjects who have experience researching and purchasing similar consumer electronics item online rated the information stimuli as being realistic to what they would anticipate viewing.

Secondly, product information breadth and depth did influence the perceived cognitive effort with the task. Given this result, in addition to the finding that cognitive effort is negatively associated with decision satisfaction; online retailers may need to be mindful of the product assortments and respective product information provided to consumers. Although recent studies indicate many consumers search online for consumer electronic product information, providing too much information may not have desirable results. Recent studies suggest that purchase cost is positively related to search time spent on the Internet (Burns 2006d). Although the greater the amount of information collected may help to mitigate the consumer's perceived risk with the purchase decision, at what point does cognitive effort hit a threshold where doubt with making a decision starts to manifest? The good news is that product involvement and choice involvement directly mitigate perceived cognitive effort under similar informational load conditions. So those consumers who are seriously searching for information may be less likely to perceive high cognitive effort with the task. On a related note, Maximizers tended to be more satisfied with their decision as compared to Satisficers. From a theoretical standpoint, information processing theory of consumer choice (Bettman 1979) was supported and extended with the testing of this choice involvement construct. Although the items used to develop this construct were a reduced and modified subset of Schwartz's (2004) items, the items performed well together. These results suggest that further testing and development of the choice involvement construct may be beneficial, particularly within a marketing and decision-making domain.

On a third note, perceived crowding of informational stimuli empirically demonstrated a significant effect on cognitive effort. Typically within the environmental psychology framework, affective states of arousal may be captured, which then influence approach or avoidance behaviors (Donovan and Rossiter 1982). In this study, the impact of perceived crowding on a perceived cognitive state was demonstrated within a choice context. To the researcher's knowledge, within an online choice context, this has not been empirically tested to date. Besides the theoretical extension within the environmental psychology framework, there may be managerial implications as well. One implication is that the white space allocated to web pages may impact how easily visitors can process the information presented. The cognitive effort required to process information presented may be closely related to a website perceived ease of use. Previous studies suggest that ease of use may be an important factor in terms of perceived usefulness and the likelihood to revisit site (Agarwal and Karahanna 2000; Venkatesh and Davis 1996; Davis 1989).

A fourth point is that cognitive effort performed as well or better than traditional information load variables in predicting choice quality outcomes. Although the variance accounted for was minimal, what the results do demonstrate is that this construct may be helpful in future studies to better understand perceptual influences on decision-making.

Just as the environmental psychology domain takes into account how a person's perception of the situation influences behavior, perhaps the examination of perceptual states within the consumer decision making context should be given more attention.

Related to decision outcomes, perceived cognitive effort with the task demonstrated considerable influence on decision satisfaction. This may mean not displaying all of the products that are available, online or offline, unless the customer can drill down to a subset that is easy to manage. Previous field research in a store setting demonstrated that fewer sales occurred when a larger assortment of product was presented (Iyengar and Leeper 2000). Online, research suggests that reducing consumers' search costs enhances the shopping experience (Lynch and Ariely 2000).

Lastly, the study suggests that there is no relationship between time spent on the task and perceived cognitive effort. One immediate implication is that time spent has been used as a proxy for cognitive effort in previous studies (Edell and Garbarino 1997). This result suggests there may be several moderators or mediators influencing the time spent. As mentioned, some subjects commented on being overwhelmed and thus just picking a product to end the task. This behavior could be explained within the environmental psychology framework: the information load (stimulus) elicited an undesirable state (organism), which led to the person avoiding the continued interaction by ending it (response). Other influencers may include the various decision strategies employed by subjects. These decision strategies, in turn, may be influenced by the information presented, in addition to other situational or personal traits (Payne, Bettman, and Johnson 1993).

CHAPTER 6

CONCLUSIONS AND FUTURE DIRECTIONS

IMPLICATIONS FOR PRACTICE

These results suggest that there are firm controlled factors (product breadth, depth, and density) and individual factors (product involvement and choice involvement) that elicit consumer perceptions to form cognitive states. This cognitive effort state in turn influences choice outcomes and satisfaction with the decision. From an online retailer perspective, how a firm presents product information may influence the perceived cognitive effort associated with the search and selection task. If a firm presents product information in a way that increases perceived cognitive effort, lower choice quality and decision satisfaction may result. One managerial implication suggested from this result, is that marketers should position their product alternatives so it is easy for the consumer to make a smart choice. This may mean not displaying all of the products that are available, online. Besides testing websites for overall perceived ease of use, testing websites for the ease of being able to process the information presented on each web page may also be beneficial. If website informational design efforts increase choice quality and choice satisfaction, then higher loyalty to the site and the firm may result.

IMPLICATIONS FOR RESEARCH

The study suggests that there is no relationship between time spent on the task and perceived cognitive effort. One immediate implication is that time spent has been used as a proxy for cognitive effort in previous studies (Edell and Garbarino 1997). What this result suggests is that there may be several moderators or mediators influencing the time spent.

The construct, cognitive effort, demonstrated good reliability within this choice experiment. In addition a modified scale for choice involvement was developed and also demonstrated good reliability. Both of these measures may be worthwhile constructs used to further test different types of marketing exchanges.

Cognitive effort performed as well or better than traditional information load variables in predicting choice quality outcomes. Although the variance accounted for was minimal, what the results do demonstrate is that this construct may be helpful in future studies to better understand perceptual influences in decision making. Just as the environmental psychology domain takes into account how a person's perception of the situation influences behavior, perhaps the examination of perceptual states within the consumer decision making context should be given more attention. As an example, in this study perceived crowding demonstrated an effect on cognitive effort within a choice context. Examination and integration across variables used in different theoretical frameworks may yield a more integrated and robust picture of the phenomena under study.

LIMITATIONS

The results of the study cannot be extrapolated to the general population, given the sample may not be entirely representative of all U.S. consumers. The sample, however, does align with the profile of many U.S. Internet users.

Ideally respondents distributed more evenly across all treatment conditions would have added more statistical robustness in testing the hypotheses. As noted by Cohen, Cohen, Aiken, and West (2003), the sample size required to adequately detect interaction effects, if they do exist, can be substantial. The inability to detect an interaction due to a limited response range, wide variance, or skewed distribution of scores across measures are just a few of the factors a researcher cannot anticipate, especially when working with new measures.

Another limitation is that the study required all subjects to view all web pages of the product prior to making a selection. So although this requirement helps to achieve the objective of the experiment, external validity is compromised. In reality, consumers may not view all product pages when performing an online product search within a web site.

Also within the context of the experiment, only one product was used. Results cannot be extrapolated to other product offered online. Additionally the impact of price and brand name presence was not tested. These two factors may play very important roles in one's overall search and selection process.

Another limitation to be noted is that density manipulation checks were not significant between high and low conditions. This result limited the power to test the perceptions of crowding and interaction effects with other product information conditions (Cohen et al 2003).

FUTURE DIRECTIONS

Based upon the results discussed, extensions of this research could follow several avenues. First, measurements of traditional and structural load could be calculated and analyzed to determine their influence on cognitive effort and if one method of measurement is a superior predictor to the other. Another avenue is to compare how the situational trait of product involvement compares to the Maximizer/Satisficer personality trait of choice involvement and to examine their relative influence on cognitive effort.

Beyond the data captured in this study, other outcome variables can be captured and analyzed. Examples include attitude toward the retailer, perceived usefulness of the information presented and the perceived ease of use of processing the information presented. These constructs could then be implemented and exploratory relationships could be tested. Another extension would be to see how consumers across different age groups vary. Given that cognitive processing is purported to decline steadily over time, how this may impact processing by consumers with different capabilities may also be insightful.

Online retailers vary in the way they present their merchandise information. Another possible extension would be to compare how a matrix layout (as conducted in this study) and presenting products with a vertical orientation (e.g. scrolling down one product at a time) influence cognitive effort and the perceived usefulness of the information presented.

TABLES

Table 1 Overload Model

Model	Environmental Focus	Mediators	Response
Overload	Number of interactions	Intensity of stimuli	Attention allocation
	Spatial construction	Complexity	Attention capacity
	Environmental demands	Novelty	Cognitive fatigue
		Unfamiliarity	

Adapted from Comparison Models of Crowding, p 558 Ch. 14 "Crowding", Baum and Paulus, Stokols and Altman editors, 1987.

Table 2 Pre-test Cognitive Effort

Cronbach's Alpha	N of Items
.894	5

Table 3 Pre-test Product Involvement

Cronbach's Alpha	N of Items
.917	8

Table 4 Pre-test Choice Involvement

Cronbach's Alpha	N of Items
.548	8

Table 5 Pilot test manipulation checks

Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F	Sig.
Hi/Hi/Hi vs Low/Low/Low	Breadth Manipulation Check-Too few:Too many	13.829(a)	1	13.829	18.344	.000
	Depth manipulation check-Too few:Too many	8.096(b)	1	8.096	8.767	.006
	Crowding manipulation check-Spacious:Crowded	7.163(c)	1	7.163	5.329	.029

Table 6 Pilot test Choice Involvement

Choice Involvement Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.464	.453	7

Table 7 Information Load – Cognitive Effort

[illegible]

[illegible]			N
[illegible]			[illegible]
H		[illegible]	[illegible]
[illegible]	0		[illegible]

Table 8 Cognitive Effort – Decision Satisfaction

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.658(a)	.432	.415	1.153

a Predictors: (Constant), Cognitive effort scale w/o ability to distinguish differences

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	32.400	1	32.400	24.372	.000(a)
	Residual	42.541	32	1.329		
	Total	74.941	33			

a Predictors: (Constant), Cognitive effort scale w/o ability to distinguish differences
b Dependent Variable: Selection satisfaction

Table 9 Top 10 states of Respondents

State	*N*	*%Total*
TX	27	10.07
CA	23	8.58
FL	21	7.84
PA	16	5.97
OH	15	5.6
IL	13	4.85
NY	11	4.1
WI	10	3.73
MI	9	3.36
MA	8	2.99
Total	153	57

Table 10 Respondents' Education Profile

Education	N	% Total
Some H.S.	8	**3%**
High School	45	**17%**
Some College	118	**44%**
4 yr college degree	51	**19%**
Some grad school	15	**6%**
Graduate school or higher	31	**12%**
Total	**268**	**100%**

Table 11 Respondents' Years of Internet Use

Internet use years	% Respondents
<= 7 years	**29%**
8-10 years	**37%**
>10-15 years	**29%**
Total	**95%**

Table 12 Multivariate Tests – Breadth Manipulation check

Effect		Value	F	Hypothesis df	Error df	Sig.
Breadth	Pillai's Trace	.139	21.411(a)	2.000	265.000	.000
	Wilks' Lambda	.861	21.411(a)	2.000	265.000	.000
	Hotelling's Trace	.162	21.411(a)	2.000	265.000	.000
	Roy's Largest Root	.162	21.411(a)	2.000	265.000	.000

a Exact statistic
b Design: Intercept+Breadth

Table 13 Depth Manipulation check

Effect		Value	F	Hypothesis df	Error df	Sig.
Depth	Pillai's Trace	.082	11.883(a)	2.000	265.000	.000
	Wilks' Lambda	.918	11.883(a)	2.000	265.000	.000
	Hotelling's Trace	.090	11.883(a)	2.000	265.000	.000
	Roy's Largest Root	.090	11.883(a)	2.000	265.000	.000

a Exact statistic
b Design: Intercept+Depth

Table 14 Density – Crowding Scores

Dependent Variable: total crowding score

density	Mean	Std. Deviation	N
low abbreviations	6.28	2.117	167
high words written out	6.26	2.212	101
Total	6.27	2.149	268

Table 15 Descriptive Statistics – Perceptions of Crowding

Dependent Variable: total crowding score

density	depth condition	Mean	Std. Deviation	N
low abbreviations	low 5 features	5.98	2.019	81
	high 15 features	6.57	2.178	86
	Total	6.28	2.117	167
high words written out	low 5 features	5.78	2.377	54
	high 15 features	6.81	1.884	47
	Total	6.26	2.212	101
Total	low 5 features	5.90	2.162	135
	high 15 features	6.65	2.075	133
	Total	6.27	2.149	268

Table 16 Depth & Density – Total Crowding Score

Dependent Variable: total crowding score

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	38.489(b)	2	19.244	4.269	.015
Intercept	9915.041	1	9915.041	2199.420	.000
Density	.012	1	.012	.003	.959
Depth	38.453	1	38.453	8.530	.004
Error	1194.627	265	4.508		
Total	11777.000	268			
Corrected Total	1233.116	267			

a Computed using alpha = .05

b R Squared = .031 (Adjusted R Squared = .024)

Table 17 Breadth, Depth, and Density – Overall Information Load

Dependent Variable: overall info load score

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Observed Power(a)
Corrected Model	37.839(b)	3	12.613	8.967	.000	.996
Intercept	5462.249	1	5462.249	3883.324	.000	1.000
Density	5.284	1	5.284	3.757	.054	.489
Depth	30.159	1	30.159	21.441	.000	.996
Breadth	4.005	1	4.005	2.847	.093	.390
Error	371.340	264	1.407			
Total	6128.000	268				
Corrected Total	409.179	267				

a Computed using alpha = .05
b R Squared = .092 (Adjusted R Squared = .082)

Table 18 Overall perceived information load across treatments

Dependent Variable: overall info load score

density	depth condition	breadth condition	Mean	Std. Deviation	N
low abbreviations	low 5 features	Low 10 alts	4.00	1.109	40
		Hi 30 alts	4.29	1.146	41
		Total	4.15	1.130	81
	high 15 features	Low 10 alts	4.76	1.011	49
		Hi 30 alts	5.03	1.554	37
		Total	4.87	1.272	86
high words written out	low 5 features	Low 10 alts	4.41	1.211	29
		Hi 30 alts	4.64	1.381	25
		Total	4.52	1.285	54
	high 15 features	Low 10 alts	5.00	.953	23
		Hi 30 alts	5.17	1.090	24
		Total	5.09	1.018	47

Table 19 Reliability Statistics – Perceived web expertise

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.911	.913	4

Table 20 Perceived web expertise items

	Mean	Std. Deviation	N
find info easily on web	5.41	1.271	268
perceived expert	4.92	1.416	268
search technique savvy	5.36	1.242	268
computer and Internet comfort	5.88	1.193	268

Table 21 Reliability Statistics – Product Involvement

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.968	.968	7

Table 22 Gender differences in product involvement

Dependent Variable: product involvement total

gender	Mean	Std. Deviation	N
male	25.36	7.510	107
female	27.37	6.552	159
Total	26.56	7.009	266

Table 23 Reliability Statistics – Choice Involvement

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.769	.769	4

Table 24 Choice involvement items

	Mean	Std. Deviation	N
all other possibilities	4.96	1.382	256
high self standards	5.18	1.297	256
seek all options	5.17	1.325	256
pain search and regret	5.16	1.428	256

Table 25 Choice involvement correlation matrix

	all other possibilities	high self standards	seek all options	pain search and regret
all other possibilities	1.000	.351	.579	.406
high self standards	.351	1.000	.425	.430
seek all options	.579	.425	1.000	.533
pain search and regret	.406	.430	.533	1.000

Table 26 Choice Involvement Component Matrix

Choice Involvement	Component
	1
all other possibilities	.763
high self standards	.698
seek all options	.840
pain search and regret	.772

Extraction Method: Principal Component Analysis.
One component extracted.

Table 27 Choice Involvement Factor Analysis

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.371	59.264	59.264	2.371	59.264	59.264
2	.684	17.106	76.370			
3	.558	13.951	90.320			
4	.387	9.680	100.000			

Extraction Method: Principal Component Analysis.

Table 28 Reliability Statistics – Cognitive Effort

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.952	.952	5

Table 29 Item-Total Statistics – Cognitive Effort

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
compare alternatives	15.31	38.941	.854	.730	.943
evaluate attributes	15.47	40.527	.869	.762	.940
distinguish betw alts	15.45	39.529	.877	.772	.939
select best	15.11	40.190	.846	.720	.944
compare attributes	15.34	39.819	.892	.799	.936

Table 30 Treatment – Choice Quality Means

Dependent Variable: Choice quality

treatment	Mean	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
HHH	.714	.048	.620	.808
HHL	.664	.039	.587	.741
HLL	.755	.039	.679	.831
HLH	.620	.048	.526	.714
LHH	.814	.050	.716	.911
LHL	.783	.034	.715	.850
LLH	.817	.043	.732	.903
LLL	.855	.038	.780	.930

Table 31 Overall Treatment – Choice Quality

	Sum of Squares	df	Mean Square	F	Sig.
Contrast	1.604	7	.229	3.575	.001
Error	18.655	291	.064		

Table 32 Product Information Breadth – Cognitive Effort

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	16.626	.627		26.525	.000
	breadth condition	5.207	.909	.333	5.729	.000

a Dependent Variable: cognitive effort total (Adjusted R squared =0.108)

Table 33 Breadth & Choice Involvement – Cognitive Effort

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	19.105	.472		40.483	.000
	Brdth2	2.390	.472	.306	5.064	.000
	CI Centered	-.273	.114	-.146	-2.394	.017
	breadth2xCI	-.018	.114	-.009	-.158	.874

a Dependent Variable: cognitive effort total

Table 34 Breadth & Product Involvement – Cognitive Effort

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	19.169	.444		43.178	.000
	Brdth2	2.237	.444	.286	5.040	.000
	centered product involvement	-.299	.063	-.270	-4.746	.000
	breadth2xproduct involv	-.035	.063	-.031	-.561	.575

a Dependent Variable: cognitive effort total

Table 35 Depth – Cognitive Effort

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	18.000	.668		26.936	.000
	depth condition	2.353	.949	.150	2.481	.014

a Dependent Variable: cognitive effort total (.019 Adjusted R squared)

Table 36 Depth & Choice Involvement – Cognitive Effort

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	19.053	.481		39.639	.000
	Depth2	1.032	.481	.132	2.147	.033
	depth2 x CI	-.085	.116	-.045	-.731	.466
	CI Centered	-.372	.116	-.198	-3.213	.001

a Dependent Variable: cognitive effort total

Table 37 Depth & Product Involvement – Cognitive Effort

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	19.098	.451		42.386	.000
	Depth2	1.212	.451	.155	2.691	.008
	centered product involvement	-.356	.064	-.321	-5.553	.000
	depth2 x product involv	.078	.064	.071	1.221	.223

a Dependent Variable: cognitive effort total

Table 38 Density – Cognitive Effort

Dependent Variable: cognitive effort total

Source	Type IV Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	.720(a)	1	.720	.012	.914
Intercept	91350.698	1	91350.698	1487.306	.000
Density	.720	1	.720	.012	.914
Error	16153.529	263	61.420		
Total	112848.000	265			
Corrected Total	16154.249	264			

a R Squared = .000 (Adjusted R Squared = -.004)

Table 39 Manipulated sub-sample/Density – Cognitive Effort

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	65.056	1	65.056	1.064	.305(a)
	Residual	6725.435	110	61.140		
	Total	6790.491	111			

a Predictors: (Constant), density
b Dependent Variable: cognitive effort total
c Selecting only cases for which crowding spacious:crowded >= 4

Table 40 Perceived Crowding (full sample) – Cognitive Effort

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	11.478	1.395		8.231	.000
	crowding spacious:crowded	2.273	.393	.336	5.781	.000

a Dependent Variable: cognitive effort total (Adjusted R squared = .109)

Table 41 Density & Choice Involvement – Cognitive Effort

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	19.052	.501		38.018	.000
	Density2	.049	.501	.006	.098	.922
	density2XCI	.048	.124	.025	.384	.701
	CI Centered	-.384	.124	-.204	-3.088	.002

a Dependent Variable: cognitive effort total

Table 42 Density, Choice Involvement, Density x Choice Involvement – Cognitive Effort

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	708.588	3	236.196	3.994	.008(a)
	Residual	14726.637	249	59.143		
	Total	15435.225	252			

a Predictors: (Constant), CI Centered, Density2, density2XCI
b Dependent Variable: cognitive effort total

Table 43 Density (manipulated sub sample) & Choice Involvement – Cognitive Effort

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	120.807	2	60.404	.987	.376(a)
	Residual	6183.106	101	61.219		
	Total	6303.913	103			

a Predictors: (Constant), CI Centered, Density2
b Dependent Variable: cognitive effort total
c Selecting only cases for which crowding spacious:crowded > 3

Table 44 Perceived Crowding & Choice Involvement – Cognitive Effort

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	19.125	.461		41.450	.000
	Choice Involvement	-.341	.111	-.182	-3.067	.002
	Perceived crowding	2.078	.405	.305	5.128	.000
	choice involvement x crowding - both centered	.049	.090	.032	.542	.588

a Dependent Variable: cognitive effort total

Table 45 Density & Product Involvement – Cognitive Effort

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	19.121	.471		40.597	.000
	Density2	.073	.471	.009	.154	.878
	density2xProdInvolv	-.038	.068	-.034	-.553	.581
	centered product involvement	-.367	.068	-.331	-5.379	.000

a Dependent Variable: cognitive effort total

Table 46 Density & Product Involvement (sub-sample) – Cognitive Effort

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	21.807	.737		29.601	.000
	Density2	.484	.737	.061	.657	.512
	density2xProdInvolv	.024	.104	.023	.233	.816
	centered product involvement	-.306	.104	-.290	-2.955	.004

a Dependent Variable: cognitive effort total
b Selecting only cases for which crowding spacious:crowded > 3

Table 47 Crowding & Product Involvement – Cognitive Effort

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	19.097	.435		43.862	.000
	centered product involvement	-.321	.062	-.290	-5.157	.000
	centered crowding check	2.066	.380	.305	5.442	.000
	product invovlement x crowding -both centered	.006	.048	.007	.120	.905

a Dependent Variable: cognitive effort total

Table 48 Cognitive Effort – Choice Quality

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.919	.038		24.120	.000
	cognitive effort total	-.007	.002	-.239	-3.997	.000

a Dependent Variable: Choice quality (Adjusted R squared = 0.54)

Table 49 Cognitive Effort – Time Spent

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	164.598	56.038		2.937	.004
	cognitive effort total	3.282	2.716	.074	1.209	.228

a Dependent Variable: total time in sec

Table 50 Cognitive Effort – Choice Satisfaction

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	6.900	.191		36.149	.000
	cognitive effort total	-.097	.009	-.544	-10.521	.000

a Dependent Variable: choice satisfaction (Adjusted R squared =0.294)

Table 51 Overall Model Information Load (Breadth, Depth, Crowding) – Choice Quality

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1.413	3	.471	8.823	.000(a)
	Residual	13.938	261	.053		
	Total	15.351	264			

a Predictors: (Constant), crowding spacious:crowded, breadth condition, depth condition
b Dependent Variable: Choice quality

Table 52 Information Load (Breadth, Depth, Crowding) – Choice Quality

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.934	.045		20.721	.000
	breadth condition	-.125	.029	-.259	-4.377	.000
	depth condition	-.021	.029	-.045	-.736	.463
	crowding spacious:crowded	-.026	.013	-.123	-2.028	.044

a Dependent Variable: Choice quality

Table 53 Overall Model: Breadth, Crowding, & Cognitive Effort – Choice Quality

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1.613	3	.538	10.212	.000(a)
	Residual	13.739	261	.053		
	Total	15.351	264			

a Predictors: (Constant), cognitive effort total, breadth condition, crowding spacious:crowded
b Dependent Variable: Choice quality

Table 54 Breadth, Crowding, and Cognitive Effort – Choice Quality

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.972	.049		19.954	.000
	breadth condition	-.104	.030	-.216	-3.472	.001
	crowding spacious:crowded	-.019	.013	-.091	-1.467	.143
	cognitive effort total	-.004	.002	-.137	-2.082	.038

a Dependent Variable: Choice quality

Table 55 Overall Model: Breadth and Cognitive Effort – Choice Quality

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1.499	2	.750	14.179	.000(a)
	Residual	13.852	262	.053		
	Total	15.351	264			

a Predictors: (Constant), breadth condition, cognitive effort total
b Dependent Variable: Choice quality

Table 56 Breadth and Cognitive Effort – Choice Quality

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.926	.037		24.758	.000
	cognitive effort total	-.005	.002	-.168	-2.703	.007
	breadth condition	-.103	.030	-.213	-3.425	.001

a Dependent Variable: Choice quality

Table 57 Depth – Choice Quality

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.055	1	.055	.940	.333(a)
	Residual	16.900	290	.058		
	Total	16.955	291			

a Predictors: (Constant), depth condition
b Dependent Variable: Choice quality

Table 58 Depth & Cognitive Effort – Choice Quality

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.924	.039		23.539	.000
	cognitive effort total	-.007	.002	-.234	-3.869	.000
	depth condition	-.016	.029	-.033	-.553	.581

a Dependent Variable: Choice quality

Table 59 Summary of Hypotheses Results

Hypothesis	Independent	Moderator	Dependent	Supported?	*Variance*
H1	Breadth		Cognitive Effort	Yes	*10%*
H1a	Breadth	CI	Cognitive Effort	No	*n/a*
H1b	Breadth	PI	Cognitive Effort	No	*n/a*
H2	Depth		Cognitive Effort	Yes	*2%*
H2a	Depth	CI	Cognitive Effort	No	*n/a*
H2b	Depth	PI	Cognitive Effort	No	*n/a*
H3	Density		Cognitive Effort	No	*n/a*
H3 1	Density		Cognitive Effort	No	*n/a*
H3 2	Crowding		Cognitive Effort	Yes	*10%*
H3a	Density	CI	Cognitive Effort	No	*n/a*
H3a 1	Density	CI	Cognitive Effort	No	*n/a*
H3a 2	Crowding	CI	Cognitive Effort	No	*n/a*
H3b	Density	PI	Cognitive Effort	No	*n/a*
H3b 1	Density	PI	Cognitive Effort	No	*n/a*
H3b 2	Crowding	PI	Cognitive Effort	No	*n/a*
H4	Cognitive Effort		Choice Quality	Yes	*6%*
H5	Cognitive Effort		Time	No	*n/a*
H6	Cognitive Effort		Choice Sat	Yes	*30%*

CI = Choice Involvement, PI=Product Involvement, ChoiceQ = Choice Quality, Choice Sat = Choice Satisfaction.

FIGURES

FIGURE 1 Conceptual Model

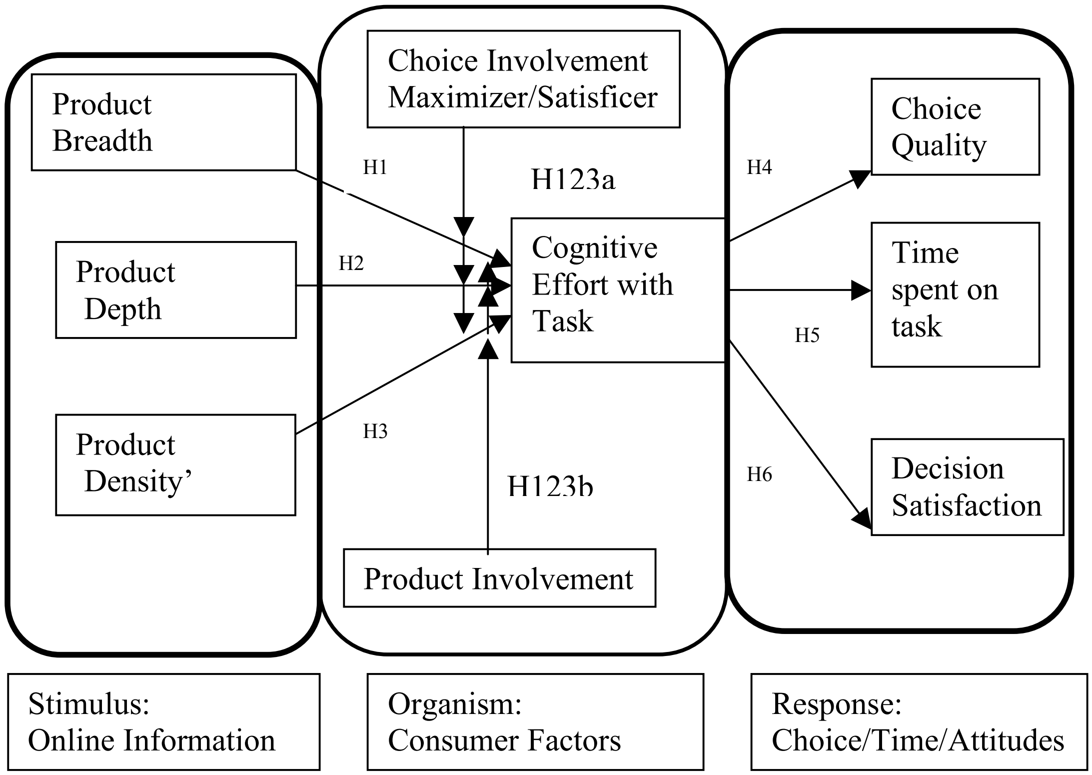
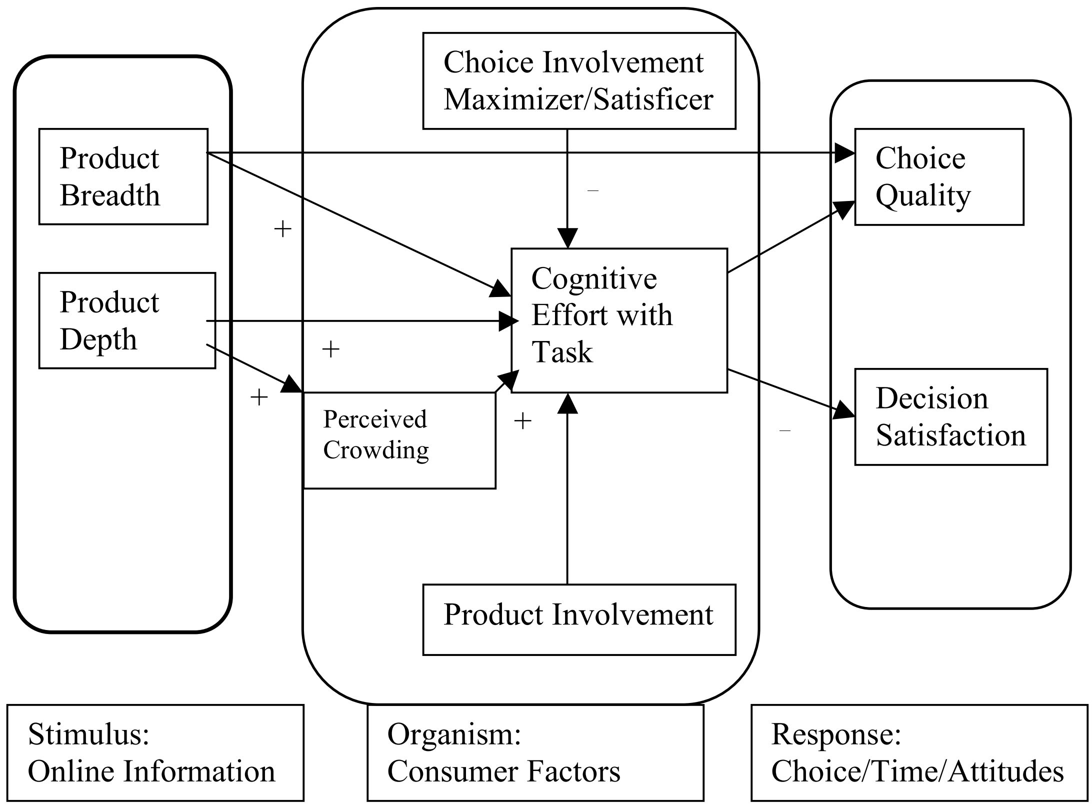


FIGURE 2 Experimental Matrix

<table>
<tr><th colspan="2">BREADTH</th><th>DEPTH</th><th colspan="2">DENSITY</th></tr>
<tr><td rowspan="5">Website Product Information Load
Products Breadth/#Alternatives
Low (10 alternatives)/ High (30 alternatives)</td><td></td><td></td><td>Low</td><td>High</td></tr>
<tr><td rowspan="2"># Pages
High – 6 pages</td><td>Low
(5 attributes)</td><td>HLL (30 alts/5attrib each)[150]</td><td>HLH (30 alts/5attrib each)[150])</td></tr>
<tr><td>High
(15 attributes)</td><td>HHL (30alts/15attrib each) [450]</td><td>HHH (30 lts/15attrib each) [450]</td></tr>
<tr><td rowspan="2"># Pages
Low – 2 pages</td><td>Low
(5 attributes)</td><td>LLL (10alts/5attrib each) [50])</td><td>LLL (10alts/5attrib each) [50]</td></tr>
<tr><td>High
(15 attributes)</td><td>LHL (10alts,15attrib each) [150]</td><td>LHH (10alts,15 attrib each)[150]</td></tr>
</table>

[#] indicates the number of informational pieces provided across the total number of pages. Ex: # alternatives x # attributes per alternative = total # of informational pieces
L=Low, H=High, sequence = breadth, depth, and density

FIGURE 3 Empirical Results Model



APPENDICES

APPENDIX A Pretest Post Experimental Questionnaire

Scenario

Imagine you have been hired as a professional shopper for a buyer. Your assignment is to search and select a digital camera that BEST meets the buyer's following requirements

Feature	Importance	Benefits
Size	20%	Ability to carry camera in pocket/purse easily
Picture quality (Megapixels)	20%	Take clear pictures
Weight	20%	Easy to carry/hold (lighter being better)
LCD size	20%	Ability to frame/shoot picture using LCD screen
Zoom	20%	Ability to take close-up pictures

You have gone online to a website that sells a large assortment of cameras. You've narrowed your search by inputting the price requirement. The cameras on the following page(s) are what are available at the price point given.

Evaluate the options provided and select the camera that best meets the need of the buyer based upon the criteria given above.

Indicate your selection in the space provided on the page(s) following the product assortment.

In addition, after selecting the best camera, please answer the questions that follow to describe your search and selection experience.

Please turn to the next page to begin the exercise.

Please write in the space provided the model number of the digital camera selected.

____

Please circle the number for each statement that best describes your search and selection experience.

1. The <u>product information presented</u> made it

Extremely Easy						Extremely Difficult	
1	2	3	4	5	6	7	For me to compare products
1	2	3	4	5	6	7	For me to evaluate the product features
1	2	3	4	5	6	7	For me to distinguish product differences
1	2	3	4	5	6	7	For me to select the best product
1	2	3	4	5	6	7	For me to process the features offered

2. When <u>evaluating the products</u> I felt

	Strongly Agree	Agree	Slightly Agree	Neither	Slightly Disagree	Disagree	Strongly Disagree
confident	1	2	3	4	5	6	7
confused	1	2	3	4	5	6	7
bored	1	2	3	4	5	6	7
overwhelmed	1	2	3	4	5	6	7
stressed	1	2	3	4	5	6	7
challenged	1	2	3	4	5	6	7
at ease	1	2	3	4	5	6	7
relaxed	1	2	3	4	5	6	7

3. When <u>choosing the best product</u> I felt

	Strongly Agree	Agree	Slightly Agree	Neither	Slightly Disagree	Disagree	Strongly Disagree
confident	1	2	3	4	5	6	7
confused	1	2	3	4	5	6	7
challenged	1	2	3	4	5	6	7
overwhelmed	1	2	3	4	5	6	7
stressed	1	2	3	4	5	6	7
bored	1	2	3	4	5	6	7
at ease	1	2	3	4	5	6	7
relaxed	1	2	3	4	5	6	7

4. How satisfied are you with camera chosen?

Very dissatisfied	Dissatisfied	Slightly Dissatisfied	Neither	Slightly Satisfied	Satisfied	Very Satisfied
1	2	3	4	5	6	7

Please circle the number for each of the following descriptors that best matches your [feelings/thoughts/beliefs] toward each of the following object.

5. For me, I find digital cameras to be

appealing	1	2	3	4	5	unappealing
useless	1	2	3	4	5	useful
valuable	1	2	3	4	5	worthless
significant	1	2	3	4	5	insignificant
fun	1	2	3	4	5	boring
undesirable	1	2	3	4	5	desirable
exciting	1	2	3	4	5	unexciting
boring	1	2	3	4	5	interesting

Please circle the number that best describes you in response to each of the following questions.

6. Whenever I'm faced with a choice, I try to imagine what all the other possibilities are, even the ones that are not present at the moment.

Strongly Agree	Agree	Slightly Agree	Neutral	Slightly Disagree	Disagree	Strongly Disagree
1	2	3	4	5	6	7

7. I treat relationships like clothing: I expect to try on a lot before finding the perfect fit.

Strongly Agree	Agree	Slightly Agree	Neutral	Slightly Disagree	Disagree	Strongly Disagree
1	2	3	4	5	6	7

8. When shopping, I have a hard time finding clothing that I really love.

Strongly Agree	Agree	Slightly Agree	Neutral	Slightly Disagree	Disagree	Strongly Disagree
1	2	3	4	5	6	7

9. No matter what I do, I have the highest standards for myself.

Strongly Agree	Agree	Slightly Agree	Neutral	Slightly Disagree	Disagree	Strongly Disagree
1	2	3	4	5	6	7

10. I often fantasize about living in ways that are quite different from my actual life.

Strongly Agree	Agree	Slightly Agree	Neutral	Slightly Disagree	Disagree	Strongly Disagree
1	2	3	4	5	6	7

11. I never settle for second best.

Strongly Agree	Agree	Slightly Agree	Neutral	Slightly Disagree	Disagree	Strongly Disagree
1	2	3	4	5	6	7

12. When I watch TV, I channel surf, often scanning through the available options even while attempting to watch one program.

Strongly Agree	Agree	Slightly Agree	Neutral	Slightly Disagree	Disagree	Strongly Disagree	Not Applicable
1	2	3	4	5	6	7	8

13. When I am listening to the radio, I often check other stations to see if something better is playing, even if I'm relatively satisfied with what I'm listening to.

Strongly Agree	Agree	Slightly Agree	Neutral	Slightly Disagree	Disagree	Strongly Disagree	Not Applicable
1	2	3	4	5	6	7	8

Please describe how you sorted through the information provided and made your final choice. Please feel free to write on the back of this sheet if you need more space.

APPENDIX B Experimental Stimuli Treatments

H-High L-Low Breadth (#alternatives)/Depth (#attributes/alternative)/Density

H/H/H – 6 pages

Consumer Electronics.com

5 of 30 camcorders

MODEL	**BC-545**	**ZQ-440**	**MM-113**	**PT-901**	**HQ-712**
Weight	1.5 pounds	2.5 pounds	2.0 pounds	1.5 pounds	2.0 pounds
Optical zoom	8x/zoom	8x/zoom	4x/zoom	4x/zoom	12x/zoom
Memory format	SDMC	HC-SDMC	HC-SDMC	SDMC	MC
LCD screen size	2.2 inches	1.7 inches	2.2 inches	2.7 inches	2.2 inches
Video resolution (pixels)	510k pixels	510k pixels	340k pixels	340k pixels	680k pixels
Built in light	Not available	Built in light	Built in light	Not available	Not available
Low light mode	Low light mode	Not available	Low light mode	Not available	Not available
Manual focus capability	Not available	Manual focus	Manual focus	Not available	Not available
Auto exposure modes	Auto exposure	Not available	Auto exposure	Not available	Auto exposure
Special effects	Not available	Special effects	Special effects	Not available	Not available
Color viewfinder	Color viewfinder	Not available	Not available	Color viewfinder	Not available
Remote control	Not available	Remote control	Not available	Remote control	Remote control
Digital still capability	Digital stills	Not available	Not available	Digital stills	Digital stills
Warranty - parts	6 months	12 months	6 months	12 months	6 months
Warranty - labor	12 months	6 months	6 months	12 months	6 months

H/H/L – 6 pages

Consumer Electronics.com

5 of 30 camcorders

MODEL	**BC-545**	**ZQ-440**	**MM-113**	**PT-901**	**HQ-712**
Weight	1.5 lbs	2.5 lbs	2.0 lbs	1.5 lbs	2.0 lbs
Optical zoom	8x	8x	4x	4x	12x
Memory format	SDMC	HC-SDMC	HC-SDMC	SDMC	MC
LCD screen size	2.2"	1.7"	2.2"	2.7"	2.2"
Video resolution (pixels)	510k	510k	340k	340k	680k
Built in light	No	Yes	Yes	No	No
Low light mode	Yes	No	Yes	No	No
Manual focus capability	No	Yes	Yes	No	Yes
Auto exposure modes	Yes	No	Yes	No	Yes
Special effects	No	Yes	Yes	No	No
Color viewfinder	Yes	No	No	Yes	No
Remote control	No	Yes	No	Yes	Yes
Digital still capability	Yes	No	No	Yes	Yes
Warranty - parts	6 mos.	12 mos.	6 mos.	12 mos.	6 mos.
Warranty - labor	12 mos.	6 mos.	6 mos.	12 mos.	6 mos.

HLH - 6 pages

Consumer Electronics.com  *5 of 30 camcorders*

MODEL	BC-545	ZQ-440	MM-113	PT-901	HQ-712
Weight	1.5 pounds	2.5 pounds	2.0 pounds	1.5 pounds	2.0 pounds
Optical zoom	8x/zoom	8x/zoom	4x/zoom	4x/zoom	12x/zoom
Memory format	SDMC	HC-SDMC	HC-SDMC	SDMC	MC
LCD screen size	2.2 inches	1.7 inches	2.2 inches	2.7 inches	2.2 inches
Video resolution (pixels)	510k pixels	510k pixels	340k pixels	340k pixels	680k pixels

HLL 6 pages

Consumer Electronics.com  *5 of 30 camcorders*

MODEL	BC-545	ZQ-440	MM-113	PT-901	HQ-712
Weight	1.5 lbs	2.5 lbs	2.0 lbs	1.5 lbs	2.0 lbs
Optical zoom	8x	8x	4x	4x	12x
Memory format	SDMC	HC-SDMC	HC-SDMC	SDMC	MC
LCD screen size	2.2"	1.7"	2.2"	2.7"	2.2"
Video resolution (pixels)	510k	510k	340k	340k	680k

LHH – 2 pages

Consumer Electronics.com  *5 of 10 camcorders*

MODEL	**PX-237**	**NK-450**	**PS-128**	**HK-322**	**AX-340**
Weight	1.5 pounds	1.5 pounds	2.5 pounds	2.0 pounds	2.5 pounds
Optical zoom	12x/zoom	4x/zoom	8x/zoom	12x/zoom	12x/zoom
Memory format	SDMC	MC	HC-SDMC	HC-SDMC	SDMC
LCD screen size	2.2 inches	2.2 inches	2.2 inches	2.2 inches	1.7 inches
Video resolution (pixels)	510k pixels	680k pixels	340k pixels	510k pixels	340k pixels
Built in light	Built in light	Built in light	Not available	Built in light	Built in light
Low light mode	Low light mode	Low light mode	Low light mode	Low light mode	Low light mode
Manual focus capability	Not available	Manual focus	Manual focus	Manual focus	Manual focus
Auto exposure modes	Not available	Not available	Auto exposure	Not available	Auto exposure
Special effects	Special effects	Not available	Not available	Not available	Not available
Color viewfinder	Color viewfinder	Not available	Not available	Not available	Not available
Remote control	Not available	Remote control	Not available	Remote control	Not available
Digital still capability	Not available	Digital stills	Digital stills	Digital stills	Not available
Warranty - parts	12 months	12 months	12 months	12 months	12 months
Warranty - labor	12 months	6 months	12 months	6 months	12 months

LLH - 2 pages

Consumer Electronics.com  *5 of 10 camcorders*

MODEL	**SQ-332**	**VX-039**	**KZ-238**	**PS-330**	**FP-380**
Weight	1.5 pounds	2.0 pounds	1.5 pounds	1.5 pounds	1.5 pounds
Optical zoom	4x/zoom	12x/zoom	12x/zoom	12x/zoom	8x/zoom
Memory format	SDMC	MC	HC-SDMC	SDMC	SDMC
LCD screen size	2.7 inches	2.2 inches	2.2 inches	2.2 inches	2.2 inches
Video resolution (pixels)	340k pixels	680k pixels	510k pixels	510k pixels	510k pixels

LHL – 2 pages

Consumer Electronics.com  *5 of 10 camcorders*

MODEL	PX-237	NK-450	PS-128	HK-322	AX-340
Weight	1.5 lbs	1.5 lbs	2.5 lbs	2.0 lbs	2.5 lbs
Optical zoom	12x	4x	8x	12x	12x
Memory format	SDMC	MC	HC-SDMC	HC-SDMC	SDMC
LCD screen size	2.2"	2.2"	2.2"	2.2"	1.7"
Video resolution (pixels)	510k	680k	340k	510k	340k
Built in light	Yes	Yes	No	Yes	Yes
Low light mode	Yes	Yes	Yes	Yes	Yes
Manual focus capability	No	Yes	Yes	Yes	Yes
Auto exposure modes	No	No	Yes	No	Yes
Special effects	Yes	No	No	No	No
Color viewfinder	Yes	No	No	No	No
Remote control	No	Yes	No	Yes	No
Digital still capability	No	Yes	Yes	Yes	No
Warranty - parts	12 mos.	12 mos.	12 mos.	12 mos.	12 mos.
Warranty - labor	12 mos.	6 mos.	12 mos.	6 mos.	12 mos.

LLL – 2 pages

Consumer Electronics.com  *5 of 10 camcorders*

MODEL	SQ-332	VX-039	KZ-238	PS-330	FP-380
Weight	1.5 lbs	2.0 lbs	1.5 lbs	1.5 lbs	1.5 lbs
Optical zoom	4x	12x	12x	12x	8x
Memory format	SDMC	MC	HC-SDMC	SDMC	SDMC
LCD screen size	2.7"	2.2"	2.2"	2.2"	2.2"
Video resolution (pixels)	340k	680k	510k	510k	510k

APPENDIX C SCALES

Product Involvement

Reliability Statistics

Cronbach's Alpha	N of Items
.963	6

Scale Items Used
unappealing:appealing
useless:useful
worthless:valuable
Insignificant:significant
boring:fun
undesirable:desirable
unexciting:exciting

Choice Involvement

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.769	.769	4

Item Statistics

	Mean	Std. Deviation	N
all other possibilities	4.96	1.382	256
high self standards	5.18	1.297	256
seek all options	5.17	1.325	256
pain search and regret	5.16	1.428	256

Cognitive Effort

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.952	.952	5

Item Statistics

	Mean	Std. Deviation	N
compare alternatives	3.86	1.806	268
evaluate attributes	3.70	1.647	268
distinguish between alternatives	3.72	1.720	268
select best	4.06	1.709	268
compare attributes	3.83	1.673	268

APPENDIX D Post Experiment Questionnaire

Introduction

The purpose of this study is to investigate how the presentation of product information may influence product choice. You are invited to participate because you may use the Internet to search for product information.

Participation in this research is voluntary. You have the right to drop out at any time.

Results from this study may help retailers design websites that are easy for consumers to use.

The records of this survey will be kept private to the extent allowed by law. Only the researcher will have access to the information you provide.

Please click the button below if you wish to continue and agree to the terms of the survey.

Scenario

You are shopping online for a **digital video camera**. The person for whom you are purchasing the digital video camera has given you the following criteria in terms of features and importance.

Feature	**Importance**	***Benefits***
Video Camera Weight	15%	*Easy to carry,* lighter being better
Video Resolution (pixels)	30%	*Picture clarity*, more pixels being better
Memory Format	10%	*Ability to record and store video information* MC-memory card (standard) SDMC-Secure digital memory card (better) HC-SDMC-High capacity SDMC (best)
LCD Screen Size	25%	*Ability to frame/shoot picture away from one's eye.* larger being better
Optical Zoom	20%	*Ability to take close-up pictures from far away.* Greater the magnification, the better.

You are at a website that sells digital video cameras. You've narrowed your selection by inputting the price requirement.

The digital video cameras presented on the following pages are what are available at the same price point.

After you evaluate the digital video cameras provided, you will be asked to select the camera that you believe BEST meets the criteria provided above.

Please note that you will <u>NOT be able to refer to this page</u> again once you start viewing the digital video cameras. (The importance weights for each feature...the more the weight, the more important the feature ...will be given again when you are asked to make your final choice)

Subject is transferred to survey site where one of eight treatment conditions are presented as outlined in Appendix A.

Post Treatment Survey Questions

While clicking through the product pages, the product information loaded

Very slowly	Slowly	Neither slowly nor quickly	Quickly	Very quickly	Don't recall

Cognitive Effort Scale Items
Please select the response for each statement that best describes your search and selection experience.

The product information presented made it

	Extremely difficult	Difficult	Somewhat difficult	Neither easy nor difficult	Somewhat easy	Easy	Extremely easy
To select the best product							
To process the features offered							
To evaluate product features							
To distinguish product differences							

To compare products							

While <u>evaluating the digital video cameras</u> I felt

	Strongly disagree	Disagree	Slightly disagree	Neither	Slightly agree	Agree	Strongly agree
relaxed							
overwhelmed							
confident							
at ease							
challenged							
confused							
bored							
stressed							

When making <u>my final product selection</u> I felt

	Strongly disagree	Disagree	Slightly disagree	Neither	Slightly agree	Agree	Strongly agree
challenged							
overwhelmed							
bored							
confident							
at ease							
stressed							
relaxed							
confused							

How satisfied are you with your video camera selection?

Completely dissatisfied	Dissatisfied	Slightly dissatisfied	Neither	Slightly satisfied	Satisfied	Completely satisfied

How confident are you that the camera you selected best meets the criteria specified?

Not confident at all	Not confident	Somewhat not confident	Neither	Somewhat confident	Confident	Completely confident

Please describe the steps you took in order to select the best product from the alternatives presented. [Free response dialogue box provided]

Manipulation Checks – Breadth, Depth, Density, and Overall Information Load

Please select the response that *best describes your evaluation on the product information* presented.

The <u>number of video cameras</u> to choose from was

Too few	Too many
Insufficient	Overwhelming

The <u>number of features</u> provided for each video camera was

Insufficient	Overwhelming
Too few	Too many

The <u>product information</u> presented on each page was

Easy to process	Hard to process
Spacious	Crowded

How would you describe the overall amount of product information presented across all the web pages.

Very small amount of information	Small amount	Somewhat small amount	Neither small nor large	Somewhat large amount	Large amount	Very large amount of information

Product Involvement Inventory Scale (Zaichkowsky 1985)

Please select the response between each pair of words that best completes your answer to the following statement.

For my own use, I find digital video cameras to be

unexciting	exciting
unappealing	appealing
boring	fun
worthless	valuable
undesirable	desirable
insignificant	significant
useless	useful

Maximizer/Satisficer Scale Items (Schwartz 2004)

Please select the response that best describes you for each of the following questions. If you feel the question is not applicable, you do not need to respond to the specific question.

Whenever I'm faced with a choice, I try to imagine what all the other possibilities are, even the ones that are not present at the moment.

Strongly disagree	Disagree	Slightly disagree	Neither agree nor disagree	Slightly agree	Agree	Strongly agree

I treat relationships like clothing: I expect to try on a lot before finding the perfect fit.

Strongly disagree	Disagree	Slightly disagree	Neither agree nor disagree	Slightly agree	Agree	Strongly agree

When shopping, I have a hard time finding clothing that I really love.

Strongly disagree	Disgree	Slightly disagree	Neither agree nor disagree	Slightly agree	Agree	Strongly agree

No matter what I do, I have the highest standards for myself.

Strongly disagree	Disagree	Slightly disagree	Neither agree nor disagree	Slightly agree	Agree	Strongly agree

I often fantasize about living in ways that are quite different from my actual life.

Strongly disagree	Disagree	Slightly disagree	Neither agree nor disagree	Slightly agree	Agree	Strongly agree

I never settle for second best.

Strongly disagree	Disagree	Slightly disagree	Neither agree nor disagree	Slightly agree	Agree	Strongly agree

When I am listening to the radio, I often check other stations to see if something better is playing, even if I'm relatively satisfied with what I'm listening to.

Strongly disagree	Disagree	Slightly disagree	Neither agree nor disagree	Slightly agree	Agree	Strongly agree

Additional Choice Involvement scale items developed and tested

Please select the response that best describes you for each of the following situations. If the situation described is not applicable to you, you do not have to respond to the question.

I generally explore *all* available product options before making a decision.

Strongly disagree	Disagree	Slightly disagree	Neither agree nor disagree	Slightly agree	Agree	Strongly agree

I generally continue to evaluate and compare my purchase decision with other similar products after the purchase has been made.

Strongly disagree	Disagree	Slightly disagree	Neither agree nor disagree	Slightly agree	Agree	Strongly agree

When there doesn't appear to be any significant differences in the products available, I will exert only the effort necessary to make a satisfactory choice.

Strongly disagree	Disagree	Slightly disagree	Neither agree nor disagree	Slightly agree	Agree	Strongly agree

I would rather feel the pain of exhaustingly searching for the best product/service upfront rather than experiencing the potential pain of making a poor decision afterwards.

Strongly disagree	Disagree	Slightly disagree	Neither agree nor disagree	Slightly agree	Agree	Strongly agree

Demographics

Please type in your current age

Please indicate your gender
Male
Female

Please type in your current residence information in the space provided
Country
State (if in U.S.)
Zipcode (if applicable)

Please indicate your highest level of education.
Some high school
High school
Some college
4 year college (B.A., B.S., etc.)
Some graduate school
Graduate school (M.A., M.S., MBA, J.D. or higher)

Covariates

Do you currently own a digital video camera?
Yes
No

Have you ever purchased a consumer electronic item online?
Yes
No

Realism Scale Item

How realistic do you think the product information presented reflects what you would expect to see when searching for this type of product online?

Not realistic at all	Completely realistic

Perceived Web Expertise Scale Items

Compared to most other people, I feel like I can find product related information easily on the Internet.

Strongly disagree	Disagree	Slightly disagree	Neither agree nor disagree	Slightly agree	Agree	Strongly Agree

I consider myself an expert in using the Internet.

Strongly disagree	Disagree	Slightly disagree	Neither agree nor disagree	Slightly agree	Agree	Strongly Agree

I consider myself knowledgeable about search techniques using the Internet.

Strongly disagree	Disagree	Slightly disagree	Neither agree nor disagree	Slightly agree	Agree	Strongly Agree

I am very comfortable using computers and the Internet.

Strongly disagree	Disagree	Slightly disagree	Neither agree nor disagree	Slightly agree	Agree	Strongly Agree

I spend a lot of time on Internet.

Strongly disagree	Disagree	Slightly disagree	Neither agree nor disagree	Slightly agree	Agree	Strongly Agree

I often use the Internet for shopping.

Strongly disagree	Disagree	Slightly disagree	Neither agree nor disagree	Slightly agree	Agree	Strongly Agree

Please type in the approximate number of years (or specify months if applicable) that you have been using the Internet.

REFERENCES

Agarwal, Ritu and Viswanath Venkatesh (2002), "Assessing a Firm's Web Presence: A Heuristic Evaluation Procedure for the Measurement of Usability," Information Systems Research, 13 (2), 168-86.

Baron, Reuben M. and David A. Kenny (1986), "The moderator-mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations," Journal of Personality and Social Psychology, 51 (6), 1173.

Baum, Andrew and Paul B. Paulus (1987), "Crowding," in Handbook of Environmental Psychology, Daniel Stokols and Irwin Altman, Eds. Vol. 1. New York: John Wiley & Sons, Inc.

Berlyne, D. E. (1958), "The Influence of Complexity and Novelty in Visual Figures on Orienting Responses," Journal of Experimental Psychology, 55, 289-96.

Bettman, James R. (1979), An Information Processing Theory of Consumer Choice: Addison-Wesley.

Bosnjak, Michael, Tracy L. Tuten, Werner W. Wittman (2005), “Unit(Non)Response in Web-Based Access Panel Surveys: An Extended Planned Behavior Approach,” Psychology & Marketing, 22 (6), 489-505.

Burns, Enid (2006a), "Active Home Web Use by Country, March 2006." April 24, 2006 ed.: www.clickz.com.

---- (2006b), "Holiday Season Dragged Online Customer Satisfaction Down." January 11, 2006 ed. Vol. 2006: www.clickz.com.

---- (2006c), "Online Retail Sales Grew," in ClickZ Stats. January 5, 2006 ed.

---- (2006d), "On Quarter of Consumer Electronics Purchases Researched Online," in ClickZStats Vol. 2007.

---- (2005e), "Retailers, Clean Up Your Online Stores." November 29, 2005 ed.: www.clickz.com.

---- (2005f), "Satisfaction with Online Shopping Dips," Vol. 2006: www.clickz.com.

Chaiken, Shelley (1980), "Heuristic versus Systematic Processing and the Use of Source versus Message Cues in Persuasion," Journal of Personality and Social Psychology (39), 752-66.

Chau, P.Y.K., G. Au, and K.Y. Tam (2000), "Impact of Information Presentation Modes on Online Shopping: An Empirical Evaluation of a Broadband Interactive Shopping Service," Journal of Organizational Computing and Electronic Commerce (10), 1-22.

Chen, Qimei, Sandra Clifford, and William D. Wells (2002), "Attitude Toward the Site II: New Information," Journal of Advertising Research (March/April), 33-45.

Cohen, Jacob, Patricia Cohen, Stephen G. West, and Leona S. Aiken (2003), "Applied Multiple Regression/Correlation Analysis for the Behavioral Sciences," Third Edition, Laurence Erlbaum Associates, Mahwah, NJ.

Cohen, S.A. (1980), "Aftereffects of Stress on Human Performance and Social Behavior: A Review of Research and Theory," Psychological Bulletin, 88, 82-108.

---- (1978), "Environmental Load and the Allocation of Attention," in Advances in Environmental Psychology, J.E. Singer & S. Valins A. Baum, Ed. Vol. 1. Hillsdale, NJ: Erlbaum.

Cook, Thomas D. and Donald T. Campbell (1979), Quasi-Experimentation; Design and Analysis Issues for Field Settings, Houghton Mifflin Boston.

Davis, Fred D. (1989), "Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology," MIS Quarterly, 13, 319-39.

Diehl, Kristin (2005), "When Two Rights Make a Wrong: Searching Too Much in Ordered Environments," Journal of Marketing Research, 42 (3), 313-22.

Diehl, Kristin and Gal Zauberman (2005), "Searching Ordered Sets: Evaluations from Sequences under Search," Journal of Consumer Research, 31 (4), 824-32.

Dillman, Don A., (2007), Mail and Internet Surveys: The Tailored Design Method. Second Edition. John Wiley & Sons, Inc. New Jersey.

Donovan, Robert J. and John R. Rossiter (1982), "Store Atmosphere: An Environmental Psychology Approach," Journal of Retailing, 58 (1), 34.

Eppler, Martin and Jeanne Mengis (2004), "The Concept of Information Overload: A Review of Literature from Organization Science, Accounting, Marketing, MIS, and Related Disciplines," Information Society, 20 (5), 325-44.

Eroglu, Sevgin A. and Karen A. Machleit (1990), "An Empirical Study of Retail Crowding: Antecedents and Consequences," Journal of Retailing, 66 (2), 201-21.

Eroglu, Sevgin and Gilbert D. Harrell (1986), "Retail Crowding: Theoretical and Strategic Implications," Journal of Retailing, 62 (4), 346-63.

Eroglu, Sevgin, Karen A. Machleit, and Lenita Davis (2003), "Empirical Testing of a Model of Online Store Atmospherics and Shopper Responses," Psychology & Marketing, 20 (2), 139-50.

Evans, Gary W. and Sheldon Cohen (1987), "Environmental Stress," in Handbook of Environmental Psychology, Daniel Stokols and Irwin Altman, Eds. New York: John-Wiley & Sons.

Gefen, David and Detmar Straub (2000), “The Relative Importance of Perceived Ease of Use in IS adoption: a Study of E-commerce Adoption,” Journal of the Association for Information Systems, (1), pages 1-28.

Gilles Laurent and Jean-Noel Kapferer (1985), “Measuring Consumer Involvement Profiles,” Journal of Marketing Research, 22, (February), 41-52

Grewal, Dhruv, Gopalkrishnan R. Iyer, and Michael Levy (2004), "Internet Retailing: Enablers, Limiters, and Market Consequences," Journal of Business Research, 57, 703-13.

Gupta, Reetika, Sucheta Nadkarni, and Stephen J. Gould (2005), ""Is this Site Confusing or Interesting?" A Perceived Web site Complexity (PWC) Scale for Assessing Consumer Internet Interactivity," Advances in Consumer Research, 32, 42-50.

Harrell, Gilbert D. and Michael D. Hutt (1976), "Buyer Behavior Under Conditions of Crowding: An Initial Framework," Advances in Consumer Research, 3 (1), 36-40.

Harrell, Gilbert D., Michael D. Hutt, and James C. Anderson (1980), "Path Analysis of Buyer Behavior Under Conditions of Crowding," Journal of Marketing Research (JMR), 17 (1), 45-51.

Helgeson, James G. and Michael L. Ursic (1993), "Information load, cost/benefit assessment and decision strategy variability," Journal of the Academy of Marketing Science, 21 (1), 13-20.

Hoffman, Donna L. (2005), "A Decade of Empirical Research on Online Consumer Behavior," in ACR Doctoral Symposium. San Antonio, TX.

Hoffman, Donna L., Thomas P. Novak, and Ann E. Schlosser (2003), "Locus of Control, Web Use, and Consumer Attitudes toward Internet Regulation," Journal of Public Policy & Marketing, 22 (1), 41.

Huang, Ming-Hui (2000), "Information Load: Its Relationship to Online Exploratory and Shopping Behavior," International Journal of Information Management, 20, 337-47.

Hui, Michael K. and John E. G. Bateson (1991), "Perceived Control and the Effects of Crowding and Consumer Choice on the Service Experience," Journal of Consumer Research, 18 (September), 174-84.

Huizingh, Eelko K.R.E. and Janny C. Hoekstra (2003), "Why Do Consumers Like Websites?" Journal of Targeting, Measurement and Analysis for Marketing, 11 (4), 350-61.

Internet Retailer (2007), “50% of Broadband Users say Internet influenced a Recent Purchase”, accessed May 15, 2007, www.Internetretailer.com/dailyNews.asp?id=21637.

Iselin, Errol R. (1993), "The Effects of the Information and Data Properties of Financial Ratios and Statements on Managerial Decision Quality," Journal of Business Finance & Accounting, 20 (2), 249-66.

Iyengar, Sheena S. and Mark R. Leeper (2000), "When Choice is Demotivating: Can One Desire Too Much of a Good Thing?" Journal of Personality and Social Psychology, 79 (6), 995-1006.

Jacoby, Jacob (1977), "Information Load and Decision Quality: Some Contested Issues," Journal of Marketing Research (JMR), 14 (4), 569.

---- (1984), "Perspectives on Information Overload," Journal of Consumer Research, 10 (4), 432-36.

Jacoby, Jacob, Donald E. Speller, and Carol Kohn Berning (1974a), "Brand Choice Behavior as a Function of Information Load: Replication and Extension," Journal of Consumer Research, 1 (1), 33-42.

Jacoby, Jacob, Donald E. Speller, and Carol A. Kohn (1974b), "Brand Choice Behavior as a Function of Information Load," Journal of Marketing Research (JMR), 11 (1), 63-69.

Jarvis, Cheryl Burke, Scott B. Mackenzie, Philip M. Podsakoff, David Glenn Mick, and William O. Bearden (2003), “A Critical Review of Construct Indicators and Measurement Misspecification in Marketing and Consumer Research,” Journal of Consumer Research, 30 (2), p199-218.

Keller, Kevin Lane and Richard Staelin (1989), "Assessing Biases in Measuring Decision Effectiveness and Information Overload," Journal of Consumer Research, 15 (4), 504-08.

---- (1987), "Effects of Quality and Quantity of Information on Decision Effectiveness," Journal of Consumer Research, 14 (2), 200-13.

Kerner, Sean Michael (2004), "Majority of US Consumers Research Online, Buy Offline," www.clickz.com.

Kirk, Roger E. (1995), Experimental Design: Procedures for the Behavioral Sciences. Pacific Grove, CA: Brooks/Cole.

Kivetz, Ran and Itamar Simonson (2000), "The Effects of Incomplete Information on Consumer Choice," Journal of Marketing Research (JMR), 37 (4), 427-48.

Kotler, Phil (1973), "Atmospherics as a Marketing Tool," Journal of Retailing, 49, 48-64.

Lazarus, R.S. (1966), Psychological Stress and the Coping Process. New York: McGraw-Hill.

Lee, Byung-Kwan and Wei-Na Lee (2004), "The Effect of Information Overload on Consumer Choice Quality in an On-Line Environment," Psychology & Marketing, 21 (3), 159-83.

Lurie, Nicholas H. (2002), "Decision Making in Information-Rich Environments: The Role of Information Structure," in Association for Consumer Research, S. Broniarczyk (Ed.) Vol. 29. Provo, UT.

---- (2004), "Decision Making in Information-Rich Environments: The Role of Information Structure," Journal of Consumer Research, 30 (4), 473-86.

Lynch, John G., and Dan Ariely (2000), “Wine Online: Search Costs Affect Competition on Price, Quality, and Distribution,” Marketing Science, 19 (1), 83-103.

Machleit, Karen A., Sevgin A. Eroglu, and Susan Powell Mantel (2000), "Perceived Retail Crowding and Shopping Satisfaction: What Modifies This Relationship?" Journal of Consumer Psychology, 9 (1), 29.

Madden, Mary (2003), "America's Online Pursuits: The Changing Picture of Who's Online and What They Do." Washington D.C.: Pew Internet and American Life Project.

---- (2006), "Internet Penetration and Impact." http://pewInternet.org: Pew Internet and American Life Project.

Malhotra, Naresh K. (1982), "Information Load and Consumer Decision Making," Journal of Consumer Research, 8 (4), 419-30.

---- (1984), "Reflections on the Information Overload Paradigm in Consumer Decision Making," Journal of Consumer Research, 10 (4), 436-41.

Malhotra, Naresh K., Arun K. Jain, and Stephen W. Lagakos (1982), "The information overload controversy: An alternative viewpoint," Journal of Marketing, 46 (2), 27-37.

McClelland, G.H., and C.M. Judd (1993), “Statistical Difficulties of Detecting Interactions and Moderator Effects,” Psychological Bulletin, 114, 376-390.

Mehrabian, Albert and James A. Russell (1974), An approach to environmental psychology. Cambridge, MA: The MIT Press.

Mendelsohn, Tamara (2006), "Understanding US Cross-Channel Shoppers," Forrester Research.

Menon, Satya and Barbara Kahn (2002), "Cross-category effects of induced arousal and pleasure on the Internet shopping experience," Journal of Retailing, 78 (1), 31-40.

Meyer, Robert J. and Eric J. Johnson (1989), "Information Overload and the Nonrobustness of Linear Models: A Comment on Keller Staelin," Journal of Consumer Research, 15 (4), 498-503.

Milgram, Stanley (1970), "The experience of living in cities," Science, Vol. 167 (3924), 1461-68.

Miller, J. A. (1956), "The Magical Number Seven Plus or Minus Two: Some Limits on our Capacity for Processing Information," Psychological Review (63), 81-97.

Moorman, Christine, Kristin Diehl, David Brinberg, and Blair Kidwell (2004), "Subjective Knowledge, Search Locations, and Consumer Choice," Journal of Consumer Research, 31 (3), 673-80.

Moschis, George P. and Jill R. Mosteller (Forthcoming), "A Conceptual Framework of Older Adults Susceptibility to Marketing Communications," Georgia State University.

Nadkarni, Sucheta and Reetika Gupta (2004), "Perceived Website Complexity, Telepresence and User Attitudes: The Moderating Role of Online User Tasks," Academy of Management Proceedings, A1.

Olson, Gary M. and Judith S. Olson (2003), "Human Computer Interaction: Psychological Aspects of the Human Use of Computing," Annual Review of Psychology, 54, 491-516.

Painton, Scott and James W. Gentry (1985), "Another Look at the Impact of Information Presentation Format," Journal of Consumer Research, 12 (September), 240-44.

Payne, John W., James R. Bettman, and Eric J. Johnson (1993), The Adaptive Decision Maker. New York, NY: Cambridge University Press.

Perdue, Barbara C., John O. Summers (1986), “Checking the Success of Manipulations in Marketing Experiments,” Journal of Marketing Research, 23, November, (4), p317-326.

Roster, Catherine., Robert D. Rogers, George C. Hozier Jr., Kenneth G. Baker, and Gerald Albaum (2007), “Management of Marketing Research Projects: Does Delivery

Method Matter Anymore in Survey Research?," Journal of Marketing Theory and Practice, 15 (2), p127-44.

Saegert, S. (1973), "Crowding: Cognitive Overload and Behavioral Constraint," in EDRA IV, W. Preiser (Ed.). Stroudsburg, PA.

---- (1978), "High-Density Environments: Their Personal and Social Consequences," in Human Response to Crowding, A. Baum & Y.M. Epstein, Ed. Hillsdale, NJ: Erlbaum.

Scammon, D.L. (1977), "'Information Load' and Consumers," Journal of Consumer Research (4), 148-56.

Sharma, Subhash, Richard M. Durand, and Oded Gur-Arie, (1981), "Identification and Analysis of Moderator Variables," Journal of Marketing Research, 18, August, 291-300.

Schulz, Axel K.-D (1999), "Experimental Research in a Management Accounting Context," Accounting & Finance, 39 (1), p29-41.

Schwartz, Barry (2004), The Paradox of Choice: Why More is Less. New York, NY: HarperCollins Publishers Inc.

Schwartz, Barry, Andrew Ward, Sonja Lyubomirsky, John Monterosso, White Katherine, and Darrin R. Lehman (2002), "Maximizing Versus Satisficing: Happiness Is a Matter of Choice," Journal of Personality and Social Psychology, 83(5), 1178-97.

Shugan, Steve (1980), "The Cost of Thinking", Journal of Consumer Research, 7 (2) 99-112.

Simonson, Itamar (1992), "The Influence of Anticipating Regret and Responsiblity on Purchase Decisions," Journal of Consumer Research, 19, 105-18.

Steuer, Jonathan (1992), "Defining Virtual Reality: Dimensions Determining Telepresence," Journal of Communications, 42 (4), 73-93.

Stokols, Daniel (1972), "On the distinction between density and crowding: Some implications for future research," Psychological Review, Vol. 79 (3), 275-77.

Suri, Rajneesh, Mary Long, and Kent B. Monroe (2003), "The Impact of the Internet and Consumer Motivation on Evaluation of Prices," Journal of Business Research, 56 (5), 379-90.

Terluin, Berlend, Willem Van Rhenen, Wilmar B. Schaufelis, and Marten De Haan (2004), "The Four-Dimensional Sympton Questionnaire (4DSQ): Measuring Distress and Other Mental Health Problems in a Working Population," Work and Stress, July, 18 (3), 187-207.

Thompson, Debora Viana, Rebecca W. Hamilton, and Roland T. Rust (2005), "Feature Fatigue: When Product Capabilities Become Too Much of a Good Thing," Journal of Marketing Research, 17 (November), 431-42.

Turley, L.W. and Ronald E. Milliman (2000), "Atmospheric Effects on Shopping Behavior: A Review of the Experimental Evidence," Journal of Business Research, 49, 193-211.

Venkatesh, Viswanath and Fred D. Davis (1996), "A Model of the Antecedents of Perceived Ease of Use: Development and Test," Decision Sciences, 27 (3), 451-81.

---- (2000), "A Theoretical Extension of the Technology Acceptance Model: Four Longitudinal Field Studies," Management Science, 46 (2), 186-204.

Wilkie, William L. (1974), "Analysis of effects of information load," Journal of Marketing Research, 11 (4), 462-66.

Yaveroglu, Idil Sayrac (2002), "A Comparison of Cue Utilization in Online and Offline Environments and the Moderating Role of Web Expertise," Georgia State University.

Yu, Julie and Harris Cooper (1983), “A Quantitative Review of Research Design Effects on Response Rates to Questionniares,” Journal of Marketing Research, 20, (February), 36-44.

Zaichkowsky, Judith Lynne (1985), "Measuring the Involvement Construct," Journal of Consumer Research, 12 (3), 341.